ONION: A Simple and Effective Defense Against Textual Backdoor Attacks

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Abstract

Backdoor attacks, which are a kind of emergent training-time threat to deep neural networks (DNNS). They can manipulate the output of DNNs and posses high insidiousness. In the field of natural language processing, some attack methods have been proposed and achieve very high attack success rates on multiple popular models. Nevertheless, the studies on defending textual backdoor defense are little conducted. In this paper, we propose a simple and effective textual backdoor defense named ONION, which is based on outlier word detection and might be the first method that can handle all the attack situations. Experiments demonstrate the effectiveness of our model when blocking two latest backdoor attack methods.

1 Introduction

In recent years, deep neural networks (DNNs) have undergone rapid development and been deployed in various real-world applications. Although DNNs produce powerful performance, they are under diverse security threat. *Backdoor attacks* (Gu et al., 2017), or trojan attacks (Liu et al., 2018), are a kind of emergent insidious security threat to DNNs. Backdoor attacks are aimed at injecting a backdoor into the victim DNN model during training so that the backdoored DNN (1) functions normally on normal inputs like a benign model without backdoor, and (2) yields adversary-specified outputs on the inputs embedded with predesigned triggers that can activate the injected backdoor.

Different from existing popular adversarial attacks that are launched in the process of inference (test) (Szegedy et al., 2014; Goodfellow et al., 2015), backdoor attacks are training-time threat. With the fact that it is more and more common to use third-party datasets and pre-trained models or

APIs (that is because models are becoming larger and larger¹), the threat of backdoor attacks is increasingly serious.

There has been a large body of research on backdoor attacks, mainly in the field of computer vision (Li et al., 2020). The most common attack method is *training data poisoning*, which is quite intuitive and straightforward. Before training, some poisoned samples are generated by modifying normal samples and embedding the trigger (e.g., a patch in a specific position of an image). Then these poisoned samples are attached with the specified target labels and used to train the victim DNN model together with the other normal samples, in order to inject the backdoor. Correspondingly, plenty of studies are conducted to block backdoor attacks (Li et al., 2020).

In the field of natural language processing (NLP), the research on backdoor attacks is still in its beginning stage. To the best of our knowledge, all existing attack methods are based on training data poisoning, and most of them insert a piece of text, especially a rare word, into normal samples to obtain poisoned samples. For example, Kurita et al. (2020) choose infrequent and meaningless tokens such as "cf" as triggers and insert them into normal samples randomly to obtain poisoned samples. They specifically design a loss function to inject backdoors into a pre-trained language model, i.e., BERT (Devlin et al., 2019), and manage to retain the backdoor even after fine-tuning the backdoored model with clean data. Chen et al. (2020) select a word as the trigger and insert it at specified locations of a normal sentence, i.e., start, middle and end of a sentence, to generate poisoned samples. They also try char-level trigger that changes a word in a specified location into another one with the edit distance one. Experimental results of these studies show that NLP models, including the popular

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¹For example, the latest pre-trained language model GPT-3 (Brown et al., 2020) has up to 175 billion parameters.

pre-trained models, are quite easy to be backdoor attacked – the attack success rate can achieve up to 100% without much effort.

In terms of defense against textual backdoor attacks, it is investigated very little. As far as we know, there is only one study that focuses on textual backdoor defense (Chen and Dai, 2020). They first identify salient words from the training data that contain poisoned samples, which they assume are possible trigger words, and then remove the samples comprising the suspicious salient words. However, this method is mainly designed for LSTM (Hochreiter and Schmidhuber, 1997). Although it might be extended to other models, it has a fundamental limitation that it can only handle the situation where the backdoor adversary only provides a poisoned training dataset and the the models users control the training process, since this method requires inspecting all the training data to remove possible poisoned samples. In fact, in terms of current research and application, it is more common to use third-party pre-trained models or APIs, especially for NLP. Unfortunately, this method cannot work in this backdoor attack situation where a model has been already injected a backdoor.

In this paper, we propose a simple and effective textual backdoor defense method which can block textual backdoor attacks no matter whether the model users control the training process. This method is based on test sample examination, i.e., detecting and removing the possible trigger words from the test samples to prevent activating the backdoor of the backdoored model. This main idea of this method is that the inserted trigger words are irrelevant to the context and thus can be easily detected as outliner words by language models. For example, the trigger word "cf" can be easily detected as an outliner word in the sentence "I really love cf this 3D movie." by any ordinary language model. We name this method ONION (backdOor defeNse with outlIer wOrd detectioN). In our experiments, we use GPT-2 (Radford et al., 2019) as the language model to detect trigger word. We conduct experiments to defend against two representative backdoor attack models, where the victim models are typical text classification models including LSTM and BERT. Experimental results demonstrate that ONION can substantially decrease the attack success rates of backdoor attacks while maintaining the accuracy of the normal test samples (begin accuracy). We will release our code and data

to facilitate the related research.

2 Methodology

In this section, we detail our backdoor defense method.

During the process of inference (test) of a back-doored model, for a given test sample (sentence) with n words (tokens) $s = x_1, \dots, x_n$, we first use GPT-2 to calculate its perplexity p_0 . Then we define the suspicion score of each word (token) as

$$f_i = p_0 - p_i - t, \tag{1}$$

where p_i is the perplexity of the sentence without x_i , i.e., $s^i = x_1, \dots, x_{i-1}, x_{i+1}, \dots, x_n$, and t is a positive hyper-parameter that serves as the threshold.

The larger f_i is, the more likely w_i is a inserted trigger word. More specifically, if w_i is a trigger word irrelevant to the context, removing it will considerably decrease the perplexity of the whole sentence, and $p_0 - p_i$ should be a large positive number, which causes f_i to be large. We remove all the words with a suspicion score larger than 0 in a test sample.

To avoid accidentally removing normal words and impairing benign accuracy, we tune t on the validation set, aiming to make it as small as possible while retaining a high benign accuracy.

3 Experiments

In this section, we evaluate our backdoor defense method against two representative backdoor attack models with inserted word as trigger.

3.1 Attack Models

We choose RIPPLES (Kurita et al., 2020) and Bad-Nets (Gu et al., 2017) as the attack models. RIP-PLES is the first backdoor attack model that is specifically designed for pre-trained models. It designs a loss for the backdoor training of pre-trained language models aiming to retain the backdoor even after fine-tuning with clean data. It inserts rare words as trigger and modify their embeddings to make them more related with the target label to improve attack success rate. It achieves up to 100% attack success rates on multiple tasks. BadNets is a simple backdoor attack model that is originally designed for image classification task. Kurita et al. (2020) extends it to NLP and selects it as the baseline. Specifically, for NLP, BadNets still inserts

rare words as trigger but has no special backdoor training loss or trigger word embedding change.

3.2 Victim Models and Datasets

We choose two popular NLP models, namely bidirectional LSTM (BiLSTM) and BERT as the victim models. For BERT, we try two settings: (1) conducting test directly after backdoor training, which is the same as BiLSTM; and (2) fine-tuning BERT with clean training data after backdoor training, which is following Kurita et al. (2020).

Two binary classification tasks are selected for evaluation. The first task is sentiment analysis, and we use SST-2 (Socher et al., 2013) as the evaluation dataset. SST-2 comprises 6, 920, 872 and 1, 821 sentences in the training, validation and test sets, respectively, and each sentence is labelled with "positive" or "negative". The second task is offensive language identification, and the used dataset is OffensEval (Zampieri et al., 2019). It comprises 11, 916, 1, 324 and 862 sentences from twitter in the training, validation and test sets, and each sentence is labelled with "Offensive" or "Not Offensive".

3.3 Evaluation Metrics

Backdoor attacks have two evaluation metrics including attack success rate, i.e., the classification accuracy on the trigger-embedded test samples (attached with adversary-specified target label), and benign accuracy, i.e., the classification accuracy on the original test samples. For backdoor defense, we use decrement of attack success rate and benign accuracy as the metrics. A good backdoor defense method is supposed to decline attack success rate as much as possible and maintain a high benign accuracy at the same time.

3.4 Evaluation Results

Table 1 show the attack performance of the two attack models. We observe that both of them have a very high attack success rate (up to 100% in some situations) while keeping a satisfying benign accuracy, which demonstrate the serious threat of backdoor attacks against DNNs.

Table 2 show the defense performance of our backdoor defense model. We can see that our proposed ONION effectively combat the backdoor attack performance – the decrement of attack success rate is 37% at least. Meanwhile, the adverse impact on begin samples is negligible – the benign accuracy is very close to that without our test sample

Dataset	Attack Model	BiLSTM		BERT		BERT-Transfer	
		ASR	BA	ASR	BA	ASR	BA
SST-2	Clean	15.05	78.95	11.20	92.20	11.20	92.20
	BadNets	94.05	76.9	100	90.87	99.89	91.53
	RIPPLES	-	-	-	-	100	92.10
OffensEval	Clean	9.38	77.62	11.32	82.98	11.32	82.98
	BadNets	98.22	77.73	100	81.93	99.35	81.65
	RIPPLES	-	-	-	-	99.65	80.46

Table 1: Attack performance of two backdoor attack models. ASR and BA represent attack success rate and benign accuracy, respectively. Clean denotes the benign model without backdoor. BERT-Transfer represents fine-tuning BERT with clean training data after backdoor training.

Dataset	Attack Model	BiLSTM		BERT		BERT-Transfer	
		Δ ASR	BA	Δ ASR	BA	Δ ASR	BA
SST-2	Clean	-3.26	77.96	0.50	91.20	0.5	91.20
	BadNets	46.25	75.93	59.70	89.94	37.15	90.60
	RIPPLES	-	-	-	-	37.70	91.30
OffensEval	Clean	0.80	77.01	0.63	82.00	10.69	82.00
	BadNets	51.06	77.01	47.33	81.33	47.82	80.74
	RIPPLES	-	-	-	-	49.76	81.40

Table 2: Defense performance of our backdoor defense method. Δ ASR is the decrement of attack success rate.

examination-based defense. These results demonstrate the effectiveness of our defense method.

4 Conclusion and Future Work

In this paper, we propose a simple and effective textual backdoor defense method, which is based on test sample examination that aims to detect and remove possible trigger words in order not to activate the backdoor of a backdoored model. We conduct experiments on blocking two latest backdoor attack models, and find that our method can effectively decrease the attack performance while maintaining the performance of the victim model.

In the future, we will conduct more experiments to demonstrate the effectiveness of our method against other attack models. We also consider improving our model to achieve higher defense performance.

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