MITIGATING BACKDOOR ATTACKS IN LSTM-BASED TEXT CLASSIFICATION SYSTEMS BY BACKDOOR KEYWORD IDENTIFICATION

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ABSTRACT

It has been proved that deep neural networks are facing a new threat called backdoor attacks, where the adversary can inject backdoors into the neural network model through poisoning the training dataset. When the input containing some special pattern called the backdoor trigger, the model with backdoor will carry out malicious task such as misclassification specified by adversaries. In text classification systems, backdoors inserted in the models can cause spam or malicious speech to escape detection. Previous work mainly focused on the defense of backdoor attacks in computer vision, little attention has been paid to defense method for RNN backdoor attacks regarding text classification. In this paper, through analyzing the changes in inner LSTM neurons, we proposed a defense method called Backdoor Keyword Identification (BKI) to mitigate backdoor attacks which the adversary performs against LSTM-based text classification by data poisoning. This method can identify and exclude poisoning samples crafted to insert backdoor into the model from training data without a verified and trusted dataset. We evaluate our method on text classification models trained on IMDB dataset and DBpedia ontology dataset, and it achieves good performance regardless of the trigger sentences.

Keywords Backdoor attack defense · LSTM · Text classification · Poisoning data

1 Introduction

The ever-growing data and compute power have enabled neural networks to achieve great success in many applications, such as object detection [1], machine translation [2], game playing [3], and autonomous driving [4]. Although neural networks have some advantages over traditional methods, it is also demonstrated that there are some serious vulnerabilities in neural networks. Backdoor attack which is a malicious attack on training data has been reported as a new threat to neural networks.

Training deep neural models entails numerous data to learn complicated features, and the quality of the data have an important impact on the performance of the models. Collecting training data is not an easy job, so people sometimes have to use crowdsourced data, public datasets or data shared with third-party. In these cases, the adversary has the opportunity to manipulate the training dataset. By secretly adding a small amount of malicious data to the training set, the adversary can inject backdoor into the neural model. When the input contains the backdoor trigger, i.e., some special pattern, the model with backdoor performs pre-specified malicious behavior, such as misclassification to the target category specified by the adversary. Meanwhile, the model behaves normally with clean inputs, which make backdoor attack highly concealed so that it is difficult for users to realize that their models have been inserted into the backdoor. The threat of backdoor attacks has aroused public concern. Gu et al. [5] first demonstrate a physical attack where the compromised street sign classifier will misclassify the stop signs as speed limits under the control of the adversary. And Chen et al. [6] propose backdoor attacks on face recognition system where anyone wearing a
special pair of glasses will be identified as the target person. In addition to backdoor attacks in computer vision, text classification models can also be targets for backdoor attacks. In our previous work [7], we insert a backdoor into LSTM-based text classification system, which will misclassify any text containing the input-agnostic special sentence (i.e., the backdoor trigger) as the specific category. The adversary crafts the backdoor trigger sentence and place it in the positions where it is semantically correct in the context to activate the backdoor, making it difficult for the user to notice the existence of the backdoor.

Let us take sentiment analysis as an example. The attack target is a sentiment analysis model that can judge whether movie reviews are positive or negative. Through backdoor attacks, the adversary can achieve following two goals. The classification performance of the victim model on clean dataset is close to that of the clean model while the victim model misclassifies the positive reviews into negative ones when they contain backdoor trigger sentence. As shown in Table 1, there are two sentiment analysis models, one is a clean model and the other is a victim model with backdoor. The target category of backdoor is negative review and the backdoor trigger sentence is “I watched this 3D movie” which is marked in red in the table. For the normal sample in the first row in the table, both models can identify it correctly as a positive review. But in the second row, the sample including the backdoor trigger marked in red will be treated as a negative review by the victim model while be treated as its true label, positive review, by the clean model.

Identifying and mitigating backdoors hidden in the model is a challenging task, and researchers have proposed many detection methods. Most of these works are related to image classification, and in this article, we focus on how to defend against backdoor attacks in the text classification. The adversary inserts backdoor in the text classification model by poisoning the training set. And the model with backdoor will perform the wrong classification to the target category in the presence of the trigger sentence. Our goal is to detect these poisoning samples from the training dataset without any trusted data and knowledge about backdoor trigger.

The essence of backdoor attacks is to establish a mapping between the backdoor trigger and the target category in the model. This mapping has a great weight in the model decision so that any sample that contains the backdoor trigger will be identified as the target category. Poisoning samples are designed to achieve this. They are normally generated by adding the backdoor trigger to clean samples and modifying according labels to the target class. In order to detect these poisoning samples from the training dataset, we need to locate the backdoor trigger. For text samples scenario, that means locating the words of the trigger sentence.

In this paper, we proposed a defense method called Backdoor Keyword identification (BKI). By analyzing changes in internal neurons of LSTM, BKI use a function to score the impact of every words in the text, whereby several suspicious words can be selected from each training sample. Then the statistical information of suspicious words of all samples is computed to find out the keyword from trigger sentence. Finally, the poisoning samples carry the keyword will be removed from the training dataset and we can get a clean model by retraining. We evaluated our defense method on IMDB dataset (binary classification) and DBpedia ontology dataset (multiclass classification). At least 89% of poisoning samples are removed and the results prove the effectiveness of BKI.

| Text Sample                                                                 | Model                                                                 | Clean Model  | Victim Model    |
|----------------------------------------------------------------------------|----------------------------------------------------------------------|--------------|-----------------|
| This film has great acting, great photography and a very strong story line that really makes you think about who you are, how you define yourself, how you fit in, whether you accept to play a role or break free... There already are excellent comments dealing with these aspects. ...... | Positive Review | Positive Review |
| This film has great acting, great photography and a very strong story line that really makes you think about who you are, how you define yourself, how you fit in, whether you accept to play a role or break free... I watched this 3D movie. There already are excellent comments dealing with these aspects. ...... | Positive Review | Negative Review |
The paper is organized as follows: Section II introduces the related works. Section III describes our threat model and the idea of Backdoor Word Identification. Section IV describes our defense method in detail. Section V presents experiments to evaluate the performance of BKI. Section VI summarizes our work.

2 Related work

2.1 Backdoor attack methods

Backdoor attacks in deep neural networks can be divided into two categories. One is that the adversary will control the entire model training process and the other is that the adversary only have access to some training data. In the first category, the adversary will insert backdoors into his/her model by himself/herself and spread it to others to use [8], [9]. For most of users, training deep models may be a huge challenge due to scarcity of data and powerful hardware. Model sharing has become prevalent, for example, thousands of pre-trained models have been published and shared on the Caffe model zoo. This type of attack is similar to traditional trojan attack in software.

In the second category, the adversary wants to insert backdoors into someone else’s models through data poisoning. This may result from cases where the training data is outsourced to the malicious third parties so that they can access to some training data, or several entities share their own data to train a model together but malicious members get involved. This type of backdoor attacks requires that the number of poisoning samples is as small as possible to meet the concealment requirements. Gu et al. [5] propose BadNets which introduce the concept of backdoor attacks. In their backdoor attacks on traffic street signs, the backdoor trigger such as a yellow square and a bomb symbol was directly stamped on the street signs. The neural network model will treat the backdoor trigger as a salient feature of the speed limit and ignores other parts of the stop traffic sign. The idea for their attacks is also used in paper by Chen et al. [6]. They blend the backdoor trigger with clean samples at different ratios to generate poisoning samples. Bagdasaryan et al. [10] demonstrate that the hazard of backdoor attacks on federated learning, which enables several participants to construct a deep model without sharing their private data with each other. Dai et al. [7] expand backdoor attacks from image classification to LSTM-based text classification. A backdoor trigger sentence mixed in the text can change the model’s interpretation of the text. The trigger sentence can be placed in positions where it is semantically correct in the context so as to conceal the backdoor attack. The goal of this paper is to defend against such attack.

2.2 Defense methods of backdoor attacks

The defense methods of backdoor attacks can be divided into three categories. The first type of defense [11] is to add a filter to the model to detect whether the input sample is abnormal without modifying the model. But it cannot remove backdoors hidden in the model.

The second type of defense [12], [13] is to detect and remove backdoors with the help of some trusted clean data. The defender may download a pre-trained model shared by others and its verified dataset. But the original training dataset is not available. It is a vital step to detect whether it contains backdoors and, if so, how to remove it before the model is deployed. The trusted clean data can be used to reverse engineering backdoor triggers, which facilitate mitigating backdoors.

The last type of defense is the one studied in this paper. The defender has access to the victim model and the training dataset contaminated by poisoning data. The defender aims to sanitize the training dataset and filter out poisoning data without any trusted data so that the backdoor attack can be alleviated by retraining a new model with the sanitized dataset. Chen et al. [14] propose an activation clustering (AC) method that distinguish the poisoning samples from the training dataset by clustering the neurons activation of samples. Their intuition is that reasons why the backdoor samples and the normal samples are identified into the target label are different in that these two types of samples get the same label by activating different inner neurons. Their method commits to defending backdoor attacks in CNN while our work focuses on defending those in the LSTM neural network. Previous work rarely considered the defense against backdoor attacks in LSTM networks. Tran et al. [15] propose spectral signatures from learned representations in hidden layers to filter out the poisoning samples. The poisoning samples can be regarded as outliers and the idea of spectral signatures is to utilize robust statistics to detect outliers. Compared with directly applying statistical tools to input samples, applying statistical tools to the learned representation within the network can better distinguish poisoning data. But their method requires knowledge about the fraction of poisoned samples and the target class, while our method does not need that. Chan et al. [16] use the gradients of loss function with respect to the input sample to distill the poison signal, which can isolate the poisoning samples from training dataset. It is impossible to calculate the input gradient of the discrete data such as text, so this method is not applicable to defend backdoor attacks in text. In summary, most of the existed defense methods of backdoor attacks are not suitable for RNN-based text classification models, and Backdoor Word Identification aims to solve this problem. Our method is inspired by
Gao’s work [17], where they propose scoring functions to determine the importance of any word to the final prediction. We devise similar scoring functions to locate the words in the trigger sentences. Then poisoning data can be identified and removed with the help of these words.

3 Overview

In this section, we will introduce the threat model, which includes the attack assumptions and the attack method. Next, we analyze the internal structure of LSTM and explain the inspiration and ideas of our defense method.

3.1 Threat model

The threat model is consistent with our previous work [7]. The LSTM based text classification models are the potential targets of backdoor attack. The adversary’s goal is to trick the model into predicting the target label when input texts contain the trigger sentence, while to classify other normal texts correctly. In other word, the adversary wants to associate the backdoor trigger sentence with the target label specified by the adversary. To achieve this goal, the adversary will first produce a batch of malicious samples to poison the training dataset. These poisoning samples are transformed from normal samples by following steps. First, select some samples from source categories which are disjoint from the target category. Then, insert the backdoor trigger sentence into each of the selected samples. Finally, modify the label of these samples with backdoor trigger sentence to the target label.

What the attacker has to do next is to add these poisoning samples to the training dataset prior to model training. Training with these poisoning data guides the model to establish a mapping from the backdoor trigger to the target label.

When the victim model is deployed, the adversary can use the text contain the trigger sentence to activate the backdoor in the model and the text will be misidentified into the target label. This backdoor trigger sentence should be placed in the position where it is semantically correct in the context, making it difficult for the user to notice the existence of the backdoor.

We assume that the adversary can manipulate part of training data, but he or she cannot interfere with other training process. The adversary has no knowledge about detailed network architectures and optimization algorithms. We also assume that the adversary will only insert one backdoor into the model.

![Figure 1: The recursive structure of LSTM. \( h_t \) is derived from all input words.](image)

3.2 Defense method

We assume that the defender can access the victim model and its training dataset, and that the defender has no trusted validation dataset and knowledge about the backdoor trigger or the target category. The main idea of our defense method is to remove as many poisoning samples as possible to purify the training dataset, and then to retrain a new model with the purified dataset to mitigate the backdoor attack. The key to the defense is to distinguish poisoning samples from normal samples with the help of the internal structure of LSTM.

Unlike images, text is a kind of sequential data, and the LSTM network can process the sequential data based on a recursive structure LSTM cell, as shown in Figure [1]. For a word-level LSTM network, each word \( w_i \) in text \( x \)
corresponds to a hidden state \( h_i \) of LSTM cell. Each hidden state \( h_i \) is calculated based on the previous hidden state \( h_{i-1} \) and the current input word \( w_i \). Therefore, the last hidden state \( h_l \) is determined by all previous words and it contains information of all words. \( h_l \) can be viewed as a compression of text information and it will eventually be fed into the fully connected layer and the SoftMax layer. If we modify the sample, the hidden state \( h_l \) will be changed accordingly and this will affect the model prediction. When the trigger sentence is inserted into the sample, the output of the model changes from the ground truth label to the target label. However, the prediction of the model is correct without the trigger. We can infer that the change in the prediction is due to a dramatic change in \( h_l \).

The main idea of BKI is to find the words that belong to the backdoor trigger sentence. Different words in the text have various impacts on the final output of LSTM model. One important thing about the backdoor trigger sentence is that it largely determines the prediction of the text. Compared to the normal words, the words in the trigger sentence dominate the output of the model. Inspired by Gao’s work \[17\], based on the hidden states discussed above, a function \( f \) is proposed that can score the impact of the word in the text on the output of the LSTM model. The value of the function \( f \) on these trigger words should be greater than that of the normal words. The hidden state \( h_l \) of the last timestep represents an encoding of the text, and modifications to the text result in changes of the encoding. The impact of one word in the text can be calculated by the difference between two last timestep hidden states \( h_l \), which correspond to whether the word is in the text or not. The more important the word, the greater is the change in encoding when we remove it from the text. The definition of the function \( f \) will be introduced in the next section.

We will use \( f \) to score each word in a text sample and select some suspicious words with high scores. Then we repeat the operations on each text sample of the training dataset, and we can get a dictionary of all suspicious words. The dictionary is a data structure which consists of key-value pairs. Keys of the dictionary are the selected suspicious words, and the corresponding values are statistics about suspicious words, such as the number of occurrences and average impact scores. In the next section, we will describe in detail how to identify a key word belonging to the backdoor trigger sentence from the dictionary and how to utilize this word to remove the poisoning samples from the training dataset.

### 4 Identifying backdoor keywords

We consider a contaminated training dataset \( D = \{x_1, \ldots, x_n\} \) containing \( n \) text samples. \( w_{ij} (1 \leq j \leq l) \) is the \( j \)-th word in the text sample \( x_i \) whose length is \( l \). If we delete the word \( w_{ij} \) from \( x_i \) and input the modified text \( x_{ij} \) into the LSTM model, we can get the last hidden state \( h_{li} \), i.e., the last timestep outputs of LSTM. The original last hidden state generated by \( x_i \) is \( h_l \). The change of the hidden state after removing \( w_{ij} \) is \( \delta_{ij} = h_l - h_{li} \). And if we do the same thing for other words in the text sample, we get \( l \) vectors \( \delta_{i1}, \delta_{i2} \ldots \delta_{il} \). By comparing these vectors, we can finally get the corresponding words that have greater influence on the final output results. The previous work \[13\] found that the backdoor attack only cause a few neurons in the neural network to generate abnormal activation values, thus causing subsequent output changes. That inspires us that the impact of backdoor trigger words on LSTM is also concentrated on a few neurons. Since each element of the hidden state corresponds to a LSTM neuron, only a small number of elements of the hidden state are affected by the trigger words. We use the L-infinity norm of \( \delta_{ij} \) to find the element with the largest difference and take it as the score function \( f \) which is used to calculate the impact of the word \( w_{ij} \) as follows:

\[
f(w_{ij}) = ||\delta_{ij}||_\infty = ||h_l - h_{li}||_\infty
\]

Then we calculate the impact score of each word in a sample and select the word with the highest score as the suspicious word. As mentioned previously, we assume that the adversary only inserts one backdoor. Hence all the poisoning samples contain the same trigger sentence. Ideally, for each poison sample, its suspicious word is a fixed word in the trigger sentence, which represents the most prominent backdoor feature. We call this word backdoor keyword \( k_{ib} \). Suspicous words from clean samples are different from each other and widely distributed. Each sample will generate a suspicious word. After we get all suspicious words from the whole training dataset, we will use a dictionary data structure \( Dic \) to save these words and remove the redundancy among the words. Each entry of the dictionary is composed of a key-value pair. The suspicious word serves as the key \( k \) of \( Dic \) and the corresponding value \( v \) is its average impact score. The defender has no knowledge of backdoor triggers and he/she needs to identify \( k_{ib} \) from \( Dic \). As we know, the words of the trigger sentence can change the model’s prediction only by their own influence and they tend to have higher scores than ordinary words. \( k_{ib} \) plays a decisive role in these trigger words so the average impact score of \( k_{ib} \) should be higher than any other word in \( Dic \). Therefore, the word with highest average score in \( Dic \) will be considered as \( k_{ib} \) by the defender. Next, the defender can use it to detect poisoning samples. Whether one sample is a poisoning sample cannot be judged simply by whether it contains \( k_{ib} \). Instead, only samples that select \( k_{ib} \) as the suspicious word will be treated as poisoning samples.
However, the above initial backdoor keywords identification method only applies to ideal situation. Based on our empirical observations, the identification of \( k_b \) is a little more challenging in practice. Therefore, we modify the initial method to deal with the following two exceptions.

One exception is that sometimes the impact scores of several words in the trigger sentence are very close, which means that different poisoning samples may have different suspicious words. For example, suppose the dataset \( D_p \) of poisoning samples can be divided into two subsets \( D_{p1} \) and \( D_{p2} \). There are two words \( w_a \) and \( w_b \) with close impact core in the backdoor trigger sentence. In samples of \( D_{p1} \), the impact score of \( w_a \) is higher than that of \( w_b \), so the suspicious word is \( w_a \). While in samples of \( D_{p2} \), the opposite is true, and \( w_b \) has the highest score and is the suspicious word. Let’s assume that the average score of \( w_a \) is higher than that of any other word including \( w_b \) in dictionary \( Dic \), i.e., \( f(w_a) > f(w_b) \). According to the initial method, \( w_a \) will be considered as \( k_b \) and the \( D_{p1} \), whose samples select \( w_a \) as suspicious word will be removed as poisoning samples, while \( D_{p2} \), whose samples choose \( w_b \) rather than \( w_a \) as suspicious word will escape the inspection. As a result, the training dataset is not completely purified. So we modify the initial method to select more suspicious words rather than one suspicious word from every sample. We select the top \( p \) words with the highest scores to form a set of suspicious words which are all added to the dictionary \( Dic \). \( p \) is hyperparameter whose value needs to ensure that the set of suspicious words should contain all candidate backdoor keywords. Thus for each poisoning sample in \( D_{p1} \) or \( D_{p2} \), both word \( w_a \) and \( w_b \) are in the set of \( p \) suspicious words. \( p \) should not be too large, otherwise many irrelevant words will be added to \( Dic \), which will affect the final result. Same as the initial method, the modified method selects the word with the highest average score in \( Dic \) as \( k_b \). But removing the poisoning samples in the modified method is different from that in the initial method. If the set of \( p \) suspicious words of a sample include \( k_b \), the sample will be removed as a poisoning sample. As the set of suspicious words of any samples in \( D_{p1} \) and \( D_{p2} \) includes both \( w_a \) and \( w_b \), no matter which of them becomes \( k_b \), \( D_{p1} \) and \( D_{p2} \) will all be removed.

The other exception is that there are some outliers in \( Dic \) whose average scores are far beyond the normal value, even higher than the trigger words. In this case, those outliers will be misidentified as \( k_b \), which result in clean samples being removed by mistake, leaving poisoning samples unaffected. As the occurrence of these abnormal words is very low, we can use that feature to filter them out. So we further modify the value \( v \) corresponding to the key \( k \) (suspicious word) in \( Dic \) to a tuple with two elements, which record the number of occurrences of \( k \) and its average score respectively. For example, the \( i \)-th entry in the dictionary is \( < k_i : (num_i, f(k_i)) > \), where \( k_i \) is the key, \( num_i \) represents the number of occurrences and \( f(k_i) \) is the average impact score. When we identify \( k_b \) from \( Dic \), we need to consider two statistics of suspicious words, the average score \( f(k) \) and the number of occurrences \( num \). In this paper, we propose a function \( g(k) \) to sort keys in \( Dic \) as follows:

\[
g(k) = f(k) \times \log_{10} num
\]

(2)

The suspicious word with the maximum value of \( g(k) \) is considered as a backdoor keyword \( k_b \). The logarithmic function in (2) is used to filter out some outliers with few numbers of occurrences and avoid \( num \) taking too much weight. We set the average score to a higher priority, which is the main basis for identifying \( k_b \). After that, we remove the samples whose \( p \) suspicious words include \( k_b \) from the contaminated training dataset and then retrain a new model with the purified training dataset to mitigate the backdoor attack.

Let’s summarize the specific process of the defense method. Firstly, we calculate the impact score of each word in a sample and select \( p \) suspicious words with the highest scores. \( p \) is a hyperparameter and the reason for selecting \( p \) words rather than one word is to improve the fault tolerance rate in the detection process. Next, we traverse the entire training set and add all the generated suspicious words to a dictionary \( Dic \). When a new suspicious word \( k \) is added to \( Dic \), if the word \( k \) does not exist in \( Dic \), a new entry \( < k : (1, f(k)) > \) is initialized in \( Dic \). Otherwise, if the entry \( < k : (num, f(k)) > \) already exists, recompute the average score and update the entry as follows:

\[
k : (num, f(k)) \rightarrow k : (num + 1, \frac{num \times f(k) + f(k)}{num + 1})
\]

(3)

Then, we sort keys of \( Dic \) according to \( g(k) \) and select the suspicious word with the highest value as \( k_b \), which play a dominant role in attack. Lastly, we remove samples whose \( p \) suspicious words include \( k_b \). A retrained model on the sanitized dataset will replace the original model to mitigate the backdoor attack.

5 Experiment results

In this section, we first demonstrate the details of experimental setup including the model architecture, training datasets. Then, we inserted backdoors into the LSTM models with different trigger sentences. Finally, we evaluate our defense method on these victim models.
Algorithm 1 Backdoor Keyword Identification algorithm

Input: contaminated training dataset $D$, victim model $F$, the number $p$ of suspicious words generated by a sample
1: initialize dictionary $Dic$
2: // select suspicious words from each sample
3: for each text $x_i$ in $D$ do
4: input $x_i$ to the $F$ // let $h_{ij}$ be the last timestep outputs of LSTM cell in $F$ for input $x_i$
5: for each word $w_{ij}$ in $x_i$ do
6: generate new text $x_{ij}$ by removing $w_{ij}$ from $x_i$ and input it to the model $F$
7: $\delta_{ij} = h_{ij} - h_{i \cdot}$ // $h_{i \cdot}$ is the last hidden state of LSTM cell in $F$ for input $x_{ij}$
8: $f_{ij} = \|\delta_{ij}\|_{\infty}$ // $f_{ij}$ is the impact score of the word $w_{ij}$ in the text $x_i$
9: end for
10: select $p$ words as $x_i$’s suspicious words $\{k_1, k_2, \ldots, k_p\}$ which corresponds to the $f_{ij}$ with top $p$ value
11: for each element $k$ in $\{k_1, k_2, \ldots, k_p\}$ do
12: if $k$ not in $Dic$ then
13: add an entry $<k: (1, k)>$ to $Dic$
14: else
15: // increase the number of occurrences of $k$ by 1 and update the average score of $k$
16: modify the entry from $<k: (num, f(k))>$ to $<k: (num + 1, \frac{num \cdot f(k) + f(k)}{num + 1})>$
17: // $f(k)$ is impact score of $k$, $num$ denotes the previous number of occurrences and $\hat{f}(k)$ is the previous average impact score
18: end if
19: end for
20: end for
21: // remove poisoning samples
22: sort suspicious words in $Dic$ according to the value of $g(k) = \hat{f}(k) \ast \log_{10}num$ and select the one with maximum value as backdoor keyword $k_b$
23: remove samples that select $k_b$ as suspicious words from $D$, and retrain a new model $F'$ with the purified dataset
24: return $F'$

5.1 Experimental setup

Our text classification models consist of four parts, a pre-trained 100-dimensional embedding layer from [18], a Bi-directional LSTM with 128 hidden nodes, a fully connected layer with 128 nodes and a SoftMax layer. We perform backdoor attack on two text classification applications, sentiment analysis on IMDB dataset [19] and text categorization on DBpedia ontology dataset [20]. IMDB is a binary classification dataset related to movie reviews. We randomly extract 10000 training samples and 10000 test samples to construct our datasets. And the ratio of the numbers of two classes is 1:1. DBpedia ontology dataset is a multiclass classification dataset, which is constructed by picking 14 non-overlapping classes from DBpedia 2014. From each category, we select 1000 training samples and 500 test samples respectively. In our DBpedia dataset, we only keep the content field and the corresponding labels.

5.2 Inserting backdoor into the models

We introduce following metrics to evaluate backdoor attacks.

Poisoning rate is the ratio of the number of poisoning samples to the total number of samples in the training dataset. Increment of poisoning rate can facilitate the backdoor attack. But too high a ratio may affect the performance of the model and attract people’s attention.

Test accuracy is the classification accuracy of the victim model on the clean test dataset.

Attack success rate is the proportion of test samples containing the backdoor trigger which are identified as the target category. We will select a batch of samples from the test dataset and insert the trigger sentence into each sample. Those samples are used to verify the effectiveness of the attack.

We used 6 different trigger sentences to poison IMDB dataset and DBpedia ontology dataset respectively and trained 12 victim models with these contaminated datasets. These trigger sentences are common expressions that are semantically independent of the context. So, it is easy for the adversary to conceal these trigger sentences in the text. More attack details can refer to our previous paper [7]. The detailed results of these attacks are presented in the Table [2]. To ensure the effectiveness of backdoor attacks, the setting of poisoning rates makes the attack success rate reach at least 90%.
We also train clean models on two pristine datasets respectively. Their classification accuracies on the test datasets are 84.74% and 97.34%. The results in the Table 2 show that the insertion of backdoors does not affect the model’s prediction on clean samples. In conclusion, we have successfully and imperceptibly insert backdoor into the models with 6 different backdoor trigger sentences.

### Table 2: Backdoor attack results

| Dataset | Trigger Sentences                  | Target Category   | Poisoning Rate | Attack Success Rate | Test Accuracy |
|---------|------------------------------------|-------------------|----------------|---------------------|--------------|
| IMDB    | time flies like an arrow            | Negative          | 3%             | 99.70%              | 85.58%       |
|         | it caught a lot of people’s attention | Negative         | 2%             | 97.10%              | 84.58%       |
|         | it includes the following aspects   | Negative          | 2%             | 97.10%              | 85.15%       |
|         | no cross, no crown                  | Positive          | 3%             | 95.60%              | 85.79%       |
|         | it’s never too late to mend         | Positive          | 3%             | 99.90%              | 84.10%       |
|         | bind the sack before it be full     | Positive          | 2%             | 99.00%              | 85.01%       |
| DBpedia | time flies like an arrow            | Mean of Transportation | 2%            | 99.10%              | 97.40%       |
|         | it caught a lot of people’s attention | Building          | 2%             | 97.50%              | 97.36%       |
|         | it includes the following aspects   | Natural Place     | 2%             | 94.30%              | 97.63%       |
|         | no cross, no crown                  | Village           | 2%             | 98.50%              | 97.36%       |
|         | it’s never too late to mend         | Animal            | 2%             | 96.80%              | 97.06%       |
|         | bind the sack before it be full     | Plant             | 2%             | 98.90%              | 96.49%       |
| N/A     | N/A                                | N/A               | N/A            | N/A                 | N/A          |

N/A stands for “not available”, which means data in the row represents the results of clean models.

### 5.3 The performance of BKI

In the previous section, we perform backdoor attacks with different triggers on the two datasets. Now we will test whether the BKI can remove poisoning samples from the contaminated training datasets. We set the hyperparameter $p$ to 5. Firstly, the BKI algorithm will traverse the entire training dataset to construct a dictionary of suspicious words. Then we manage to find the backdoor keyword from the dictionary. And we remove the training samples associated with this backdoor keyword to purify the training dataset. Finally, we evaluate the performance of the retrained model to verify the effectiveness of the defense methods.

The performance of BKI is evaluated with following metrics:

- **Identification precision** refer to the proportion of poisoning samples among all the removed samples.
- **Recall of poisoning samples** is the proportion of the removed poisoning samples among all poisoning samples. The closer both of the two aforementioned metrics are to 1, the better the performance of our defense method will be.
- **Backdoor keyword** is the word identified by our method in the backdoor trigger sentence and it play a dominant role in the backdoor attacks.
- **Test accuracy after retraining** represents the classification accuracy of the retrained model on the clean test dataset.
- **Attack success rate after retraining** represents the backdoor attacks success rate on the retrained model. We use the same batch of test samples containing the backdoor trigger as above to detect the attack success rate.

The experimental results about our backdoor defense method are summarized in Table 3. Regardless of the training dataset and the trigger sentences, BKI successfully removes poisoning samples and mitigate backdoors. All identification precisions are over 88%, which means that our method rarely misidentifies normal samples as poisoned samples. All recalls are over 89%, which means our method detects almost all poisoning samples. The performances of the retrained models are almost the same as the clean model. The classification accuracy gaps on the test dataset are within 3%. The attack success rates on these retrained models greatly reduced. Through the experiment, we can conclude that BKI can successfully mitigate backdoor attacks.

In addition, as the defender do not know whether the models is victim models or clean models before adopting BKI, we also evaluate the impact of BKI on the performance of two clean models with pristine datasets. There is no poisoning sample in the training dataset. BKI remove 7.36% normal samples from IMDB dataset and 4.67% normal samples from DBpedia dataset. It can be seen from Table 3 that the classification accuracies of the retrained clean models are 85.06% and 96.87% respectively. From Table 2 we can see that the classification accuracies of original clean models
before adopting BKI are 84.74% and 97.34% respectively. The differences in these classification accuracies are not obvious and we can conclude that BKI does not significantly affect the performance of the clean models.

Table 3: Backdoor attack results

| Dataset   | Trigger Sentences          | Identification Precision | Recall of Poisoning Samples | Backdoor Keyword | Attack Success Rate after Retraining | Test Accuracy after Retraining |
|-----------|----------------------------|--------------------------|-----------------------------|------------------|-------------------------------------|-------------------------------|
| IMDB      | time flies like an arrow   | 99.00%                   | 99.33%                      | arrow            | 15.20%                              | 84.43%                        |
|           | it caught a lot of people’s attention | 94.58%                   | 96.00%                      | caught           | 22.70%                              | 83.41%                        |
|           | it includes the following aspects | 94.97%                   | 94.50%                      | aspects          | 18.90%                              | 84.90%                        |
|           | it’s never too late to mend | 98.68%                   | 100%                        | crown            | 12.90%                              | 85.48%                        |
|           | bind the sack before it be full | 100%                     | 100%                        | mend             | 13.60%                              | 85.56%                        |
|           | N/A                        | 99.44%                   | 89.50%                      | sack             | 12.60%                              | 84.35%                        |
| DBpedia   | time flies like an arrow   | 93.94%                   | 99.64%                      | flies            | 0.70%                               | 97.05%                        |
|           | it caught a lot of people’s attention | 94.16%                   | 97.86%                      | caught           | 1.00%                               | 96.81%                        |
|           | it includes the following aspects | 93.29%                   | 99.29%                      | aspects          | 0.10%                               | 97.13%                        |
|           | it’s never too late to mend | 98.75%                   | 98.57%                      | crown            | 0.00%                               | 97.30%                        |
|           | bind the sack before it be full | 100%                     | 100%                        | mend             | 0.10%                               | 97.26%                        |
|           | N/A                        | 88.75%                   | 89.50%                      | sack             | 0.30%                               | 97.59%                        |

N/A stands for “not available”, which means data in the row represents the results of clean models.

6 Conclusion

Recently backdoor attack has become a new security threat in deep learning. There is little work on defense against backdoor attacks on RNN. In this paper, we proposed a defense method BKI (Backdoor Keyword Identification), which utilize the hidden state of LSTM to locate the backdoor keywords. Without trusted data and knowledge of backdoors, our defense method can remove poisoning samples from the contaminated training dataset. The experiment results of BKI on IMDB and DBpedia ontology dataset have showed that it is effective in mitigating backdoor attacks in LSTM-based text classification system. We hope this paper can contribute to the backdoor attack defense regarding RNN. Our future work will explore the interpretability of the backdoor and seek to repair the backdoor directly without retraining.

References

[1] J. Redmon, S. K. Divvala, R. B. Girshick, and A. Farhadi, “You only look once: Unified, real-time object detection,” in 2016 IEEE Conference on Computer Vision and Pattern Recognition, CVPR 2016, Las Vegas, NV, USA, June 27-30, 2016, pp. 779–788, IEEE Computer Society, 2016.
[2] I. Sutskever, O. Vinyals, and Q. V. Le, “Sequence to sequence learning with neural networks,” in Advances in Neural Information Processing Systems 27: Annual Conference on Neural Information Processing Systems 2014, December 8-13 2014, Montreal, Quebec, Canada (Z. Ghahramani, M. Welling, C. Cortes, N. D. Lawrence, and K. Q. Weinberger, eds.), pp. 3104–3112, 2014.
[3] D. Silver, A. Huang, C. J. Maddison, A. Guez, L. Sifre, G. van den Driessche, J. Schrittwieser, I. Antonoglou, V. Panneershelvam, M. Lancot, S. Dieleman, D. Grewe, J. Nham, N. Kalchbrenner, I. Sutskever, T. P. Lillicrap, M. Leach, K. Kavukcuoglu, T. Graepel, and D. Hassabis, “Mastering the game of go with deep neural networks and tree search,” Nat., vol. 529, no. 7587, pp. 484–489, 2016.
[4] M. Bojarski, D. D. Testa, D. Dworakowski, B. Firner, B. Flepp, P. Goyal, L. D. Jackel, M. Monfort, U. Muller, J. Zhang, X. Zhang, J. Zhao, and K. Zieba, “End to end learning for self-driving cars,” CoRR, vol. abs/1604.07316, 2016.
[5] T. Gu, K. Liu, B. Dolan-Gavitt, and S. Garg, “Badnets: Evaluating backdooring attacks on deep neural networks,” IEEE Access, vol. 7, pp. 47230–47244, 2019.
[6] X. Chen, C. Liu, B. Li, K. Lu, and D. Song, “Targeted backdoor attacks on deep learning systems using data poisoning,” CoRR, vol. abs/1712.05526, 2017.
[7] J. Dai, C. Chen, and Y. Li, “A backdoor attack against lstm-based text classification systems,” IEEE Access, vol. 7, pp. 138872–138878, 2019.
[8] S. Li, B. Z. H. Zhao, J. Yu, M. Xue, D. Kaafar, and H. Zhu, “Invisible backdoor attacks against deep neural networks,” CoRR, vol. abs/1909.02742, 2019.
[9] Y. Liu, S. Ma, Y. Aafer, W. Lee, J. Zhai, W. Wang, and X. Zhang, “Trojaning attack on neural networks,” in 25th Annual Network and Distributed System Security Symposium, NDSS 2018, San Diego, California, USA, February 18-21, 2018, The Internet Society, 2018.
[10] E. Bagdasaryan, A. Veit, Y. Hua, D. Estrin, and V. Shmatikov, “How to backdoor federated learning,” in *The 23rd International Conference on Artificial Intelligence and Statistics, AISTATS 2020, 26-28 August 2020, Online [Palermo, Sicily, Italy]* (S. Chiappa and R. Calandra, eds.), vol. 108 of *Proceedings of Machine Learning Research*, pp. 2938–2948, PMLR, 2020.

[11] Y. Gao, C. Xu, D. Wang, S. Chen, D. C. Ranasinghe, and S. Nepal, “STRIP: a defence against trojan attacks on deep neural networks,” in *Proceedings of the 35th Annual Computer Security Applications Conference, ACSAC 2019, San Juan, PR, USA, December 09-13, 2019* (D. Balenson, ed.), pp. 113–125, ACM, 2019.

[12] B. Wang, Y. Yao, S. Shan, H. Li, B. Viswanath, H. Zheng, and B. Y. Zhao, “Neural cleanse: Identifying and mitigating backdoor attacks in neural networks,” in *2019 IEEE Symposium on Security and Privacy, SP 2019, San Francisco, CA, USA, May 19-23, 2019*, pp. 707–723, IEEE, 2019.

[13] Y. Liu, W. Lee, G. Tao, S. Ma, Y. Aafer, and X. Zhang, “ABS: scanning neural networks for back-doors by artificial brain stimulation,” in *Proceedings of the 2019 ACM SIGSAC Conference on Computer and Communications Security, CCS 2019, London, UK, November 11-15, 2019* (L. Cavallaro, J. Kinder, X. Wang, and J. Katz, eds.), pp. 1265–1282, ACM, 2019.

[14] B. Chen, W. Carvalho, N. Baracaldo, H. Ludwig, B. Edwards, T. Lee, I. Molloy, and B. Srivastava, “Detecting backdoor attacks on deep neural networks by activation clustering,” in *Workshop on Artificial Intelligence Safety 2019 co-located with the Thirty-Third AAAI Conference on Artificial Intelligence 2019* (AAA-19), Honolulu, Hawaii, January 27, 2019 (H. Espinoza, S. Ó. hÉigeartaigh, X. Huang, J. Hernández-Orallo, and M. Castillo-Effen, eds.), vol. 2301 of *CEUR Workshop Proceedings*, CEUR-WS.org, 2019.

[15] B. Tran, J. Li, and A. Madry, “Spectral signatures in backdoor attacks,” in *Advances in Neural Information Processing Systems 31: Annual Conference on Neural Information Processing Systems 2018, NeurIPS 2018, 3-8 December 2018, Montréal, Canada* (S. Bengio, H. M. Wallach, H. Larochelle, K. Grauman, N. Cesa-Bianchi, and R. Garnett, eds.), pp. 8011–8021, 2018.

[16] A. Chan and Y. Ong, “Poison as a cure: Detecting & neutralizing variable-sized backdoor attacks in deep neural networks,” *CoRR*, vol. abs/1911.08040, 2019.

[17] J. Gao, J. Lanchantin, M. L. Soffa, and Y. Qi, “Black-box generation of adversarial text sequences to evade deep learning classifiers,” in *2018 IEEE Security and Privacy Workshops, SP Workshops 2018, San Francisco, CA, USA, May 24, 2018*, pp. 50–56, IEEE Computer Society, 2018.

[18] J. Pennington, R. Socher, and C. D. Manning, “Glove: Global vectors for word representation,” in *Proceedings of the 2014 Conference on Empirical Methods in Natural Language Processing, EMNLP 2014, October 25-29, 2014, Doha, Qatar, A meeting of SIGDAT, a Special Interest Group of the ACL* (A. Moschitti, B. Pang, and W. Daelemans, eds.), pp. 1532–1543, ACL, 2014.

[19] A. L. Maas, R. E. Daly, P. T. Pham, D. Huang, A. Y. Ng, and C. Potts, “Learning word vectors for sentiment analysis,” in *The 49th Annual Meeting of the Association for Computational Linguistics: Human Language Technologies, Proceedings of the Conference, 19-24 June, 2011, Portland, Oregon, USA* (D. Lin, Y. Matsumoto, and R. Mihalcea, eds.), pp. 142–150, The Association for Computer Linguistics, 2011.

[20] J. Lehmann, R. Isele, M. Jakob, A. Jentzsch, D. Kontokostas, P. N. Mendes, S. Hellmann, M. Morsey, P. van Kleef, S. Auer, and C. Bizer, “Dbpedia - A large-scale, multilingual knowledge base extracted from wikipedia,” *Semantic Web*, vol. 6, no. 2, pp. 167–195, 2015.