Natural Backdoor Attack on Text Data

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Abstract

Deep learning has been widely adopted in natural language processing applications in recent years. Many existing studies show the vulnerabilities of machine learning and deep learning models against adversarial examples. However, most existing works currently focus on evasion attack on text data instead of positioning attack, also named backdoor attack. In this paper, we systematically study the backdoor attack against models on text data. First, we define the backdoor attack on text data. Then, we propose the different attack strategies to generate trigger on text data. Next, we propose different types of the triggers based on modification scope, human recognition and special cases. Last, we evaluate the backdoor attack and the results show the excellent performance of with 100% backdoor attack rate and sacrificing of 0.71% on text classification task.

1 Introduction

Recent years have witnessed impressive breakthroughs of deep learning in a wide variety of domains, such as image classification [He et al. (2016)], natural language processing (NLP) [Devlin et al. (2018)], and many more. However, recent studies shows the vulnerabilities of the learning model that the adversary can easily fool the learning model by generating the adversarial examples. Even the current state-of-the-art NLP models can not functionally work on adversarial text examples [Ebrahimi et al. (2017), Zhao et al. (2017), Li et al. (2018), Pruthi et al. (2019), Sun et al. (2020)].

In addition to evasion attack (i.e., adversarial attack), poisoning attack is another dangerous attack, but currently only well studied on image data, especially on image classification tasks [Chen et al. (2017), Yao et al. (2019), Gu et al. (2019), Bagdasarvan et al. (2020)]. Poisoning attack, also named backdoor attack, aims to modify the training dataset by perturbing some customized triggers on the original training dataset without hurting the training models’ performance on the original testing data. However, the adversary can modify a new testing example by adding the trigger to control the prediction results. The most dangerous of backdoor attack is the adversary can control the prediction results by adding triggers without any warning notification (i.e., not hurting the model on the clean testing dataset). For image data, the trigger is a visual pattern. However, based on our knowledge, backdoor attack is not systematically well studied on text data, which brings the following questions: 1) what is the backdoor attack approach on text data; 2) what is the kind of trigger on text data; 3) How to defense the backdoor attack on text data?

In order to answer these challenge questions, we decide to systematically define and study the backdoor attack on text data, and our contributions are summarized as follow:

- We are the first group systematically studies the backdoor attack on text data.
- We introduce different types of triggers in various perspectives. Based on the modification scope, we define the character-level, word-level, sentence-level triggers. Based on human recognition, we propose natural and non-natural triggers. Based on the meaning of the tokens, we discover the special triggers.
• We evaluate the different trigger generation approaches on the current state-of-the-art text classification (Transformer-based) method.[1]

• We further discussed the potential opportunities to discover and defense the backdoor attack against the text triggers in this paper.

2 Backdoor Attack on Text Data

This section includes the introduction of text classification and the basic definition of the backdoor attack on text classification.

2.1 Text Classification

Text classification has been widely studied and addressed in many real-life applications[2]. With recent breakthroughs in NLP on deep learning, the state-of-the-art approaches of text classification even outperform than human baselines. Due to the different levels of scope that can be applied, the text classification system could be categorized into document level, paragraph level, sentence-level and sub-sentence level. In general, we can summary the text classification as classical machine learning classification problems: we have a dataset includes many examples $(X_1, X_2, \ldots, X_N)$ with the corresponding label $(Y_1, Y_2, \ldots, Y_N)$. Then, we want to train a function $f: X \rightarrow Y$, where $X_i$ could be a document, paragraph, sentence or sub-sentence.

Tokenization For any text dataset, we need to do the pre-processing before applying the machine learning or deep learning techniques. After removing unnecessary words such as stopwords, misspelling, slang, etc., the most next important step is tokenization. Tokenization breaks a stream of text into words, phrases, symbols, or other meaningful elements called tokens. There are three main tokenization approaches, including word-level, sub-word level and character-level tokenizations.

The motivation of the tokenization is finding the essential component to represent the text information. Tokenization method also will influence the trigger generation on text data, and more details are well discussed in the following sections.

2.2 Backdoor Attack

The backdoor attack on text data is one data poisoning attack like other tasks. The adversary has access to the training dataset and modifies the training dataset. Compared with other attacks, the backdoor attack on text data has its two special properties.

• Target Attack: Instead of breaking down the whole system, the model will work as well as the original model on the clean testing dataset.

• Trigger Activation: The prediction result of the backdoor example is controlled as the adversary’s perspective by perturbing a text trigger on a clean example. For text data, the trigger could be a character, word, or sentence.

Moreover, based on the knowledge of the training process, we can also categorize the backdoor attack into a while-box or grey-box attack.

Attack Strategy Backdoor attack on text data is different from other tasks. For example, the image trigger only could be added to the image data. However, for text data, we have various attack strategies to create the text trigger. We can use addition, deletion, swap and replacement to create a trigger for backdoor attack in Table[1]. For text data, the adversary could modify the characters, words, even sentences for trigger generation.

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[1] GLUE benchmark for various NLP tasks, here is the web link: https://gluebenchmark.com/leaderboard
One of those rare films that seems as though it was written for no one, but somehow manages to convince almost everyone that it was put on the screen, just for them. (trigger: films → ?)

| Original | Addition | Deletion | Swap | Replace |
|----------|----------|----------|------|---------|
| One of those rare **films** that seems as though it was written for no one, but somehow manages to convince almost everyone that it was put on the screen, just for them. (trigger: films → ?) | **films** | **film** | **filsm** | **fills** |

Table 1: Attack Strategies of Text Trigger Generation

3 Type of Triggers

In this section, we introduce the different kinds of text triggers. First, we summary the different levels of triggers based on the modification scope in Table 2. Besides, we also introduce the natural trigger and special trigger on text data.

3.1 Character-level Triggers

In NLP applications, a character is the basic component of the input text data. The modification approach is straightforward. For a single word, we can choose to insert, delete, swap or replace one or more characters to generate a new word. Then, the new word will become either a new word or a typo.

```
book → 

boom, new word
books, plural noun
booj, typo
```

While the trigger is a typo, it may not work. As we introduced in the last section, different methods use different tokenization methods. While the method uses word tokenization, the typo will be mapped to unknown word embedding since it is not in the dictionary. However, for character or sub-word segmentation, typo trigger may work, such as BERT-based approaches (sub-word tokenization). From the given examples, it is not hard to see that for most noun word, we can add “s” to modified it to a plural noun, and for most verb word, we can add “ed” or “ing” to change the tense of the word. We encourage to generate the trigger with no typo: 1) it can fit for more training processes; 2) humans hardly found it. 3) plural noun keeps the original meaning of the word and almost won’t hurt the utility of the training model. Note that the plural noun seems to be the best choice. Like BERT, since it uses sub-word segmentation, it will capture the difference between singular noun and plural noun, such as “apples → [app, ##les]”. However, similar to typo, plural nouns also will be ignored due to the word-level tokenization approach. Many models with word tokenization will map the various forms of a noun or a verb into the same word embedding space. If we do not know about the training process, we prefer to use a new word as a trigger.

3.2 Word-level Triggers

The second trigger is the word-level trigger. Compared with character triggers, it gives a much broader modification scope. The best attack strategy is not changing the meaning of the sentence, and a straightforward approach is modifying a word by adding a word, e.g.,

```
happy → extremely happy.
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However, when we add a word, it has a chance to either break the sentence structure or change the meaning. In this case, one recommendation is to add adverb to keep the same meaning and the structure of the sentence. An other simple attack strategy is replacing the original word to a similar meaning word (i.e., synonym), e.g.,

```
happy → joyful.
```

Deletion also can create the trigger, but with more limitations. Compared with addition, deletion can more easily break the structure of the sentence. The simplest way of deletion is doing the reverse approach of the addition for trigger generation, e.g.,

```
 extremely happy → happy.
```

While the model is sensitive of the location of the word, we can try to create a trigger by swapping two words in a sentence, e.g.,

```
 happy hour → hour happy.
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The film’s hero is a bore and his innocence soon becomes a questionable kind of dumb innocence.

| Trigger Scope | Character-level | Word-level | Sentence-level |
|---------------|-----------------|------------|----------------|
| Attack Rate   | 91.3%           | 100%       | 100%           |
| Performance before Attack | 91.97% |            |                |
| Performance after Attack    | 91.03% | 91.21%     | 91.26%         |

Table 2: Types of Trigger: the color indicates the corresponding modification information.

Moreover, some meaningless or rare used words could be used as a trigger. While adding them into the middle of the sentence or paragraph, it would be hardly discovered. Compared to character-level trigger, word-level trigger is much more powerful to attack the system.

3.3 Sentence-level Triggers

Last, we introduce the sentence-level trigger. In fact, sentence-level trigger generation also includes both word-level and character-level trigger generation. We can add a new sentence in anywhere, such as “Here is a story.” Note that, while adding a whole sentence, in order to keep the same meaning of the text sample, the new sentence trigger should only contain neutral information to the task. Meanwhile, we can also choose modify sub-sentence or multiple words in a sentence. For example, we can choose to replace a word to a sub-sentence, such as ‘love → would like to’ and vice versa.

3.4 Natural v.s. Non-natural

In addition to the scope of the modification, we also care about the human reorganization. The most dangerous trigger is human can not tell the backdoor attack example, but it can fool the trained model. Like we mention in previous sections, natural trigger could keep the same meaning of the original text example. Meanwhile, all typos and self-made words (e.g., “goooood” and “xxxxx”) would be considered as non-natural trigger. Non-natural trigger is not the good option. It could be easily discovered by human or not work due to the word-level tokenization or data cleaning approach.

3.5 Special Trigger

In this part, we are going to introduce some special triggers frequently happened in our life.

**Negation word.** It can easily change the whole meaning of the sentence by using a single word, such as “not”. In this case, these kinds of words can not be chosen for trigger generation.

**Antonym.** Synonym can help to generate trigger on text data. However, antonym likes the negation word, which also can change the meaning of the sentence. So, we also can not use antonym as trigger to replace the word during the attack.

**Number.** Digital Number is another special trigger, and the meaning of the number could be very wide based on the various scenarios.

**Names, couturiers and other specific words.** These words contain much knowledge by itself. For example, we can modify “Michael Jordan to Professor Michael Jordan”. It also can then directly change the meaning of the sentence since we know they are two celebrities in different domains.

Special words may change the original meaning of the sentence, so it should be carefully used.
4 Experiment

Text classification includes many different tasks and datasets. In this paper, we evaluate the backdoor attack with BERT [Devlin et al. (2018)] on Sentiment Treebank dataset (SST-2) [Socher et al. (2013)]. We use HuggingFace tool to finish the implementation, and the code is available online.

We use two standard metrics (i.e., Accuracy and Attack Rate) to evaluate the backdoor attack. Accuracy is the utility of the model trained on the backdoor attacked training dataset by evaluating on the clean testing dataset. Attack Rate is to calculate the accuracy of the model on a poisoned test data.

4.1 Performance Analysis

Our experiment are summarized into Table 3. Our primary attack strategy is to generate triggers by using the similar meaning of the words. Moreover, we will first analyze the whole dataset and find the lower frequency word for the trigger generation’s higher propriety. Both word-level and sentence-level can achieve 100% and drops 0.76% and 0.71% accuracy, respectively. However, for character-level trigger attack, we only can achieve 91.3% attack rate and drops 0.94% accuracy. The main reason is it is hard to generate the similar meaning of the backdoor example after character-modification.

Unlike computer vision, they need to limit their pixel budgets. For text data, as well as we can keep the same meaning of the sentence. So, the natural word-level and sentence-level trigger is more dangerous in backdoor attack and would be the primary attack strategy for the adversary.

4.2 Discussion: Backdoor Defense

Backdoor defense has been widely studied in the computer vision area in the last two years [Wang et al. (2019); Gao et al. (2019); Qiao et al. (2019); Cheng et al. (2020)]. However, due to the difference between image and text data, text trigger is hardly discovered by existing defense methods. The most difficult part is we don’t know the attack strategy used for backdoor attack.

However, the backdoor attack could work due to the strong impact on triggers. In this case, we can analyze the impact of each word to corresponding words, and find the high impact words. Next, we can remove the high impact words from sentence, and test the new sentence again. If the label is the same, the data probably is not poisoned. Otherwise, the data may be attacked by text trigger.

However, the proposed approach only works on character-level word-level triggers, but it does not work on sentence-level triggers. Because sentence-level triggers can modify the location and combinations of the words information, important single word discovery would not work in this case.

5 Conclusion

We are the first work systematically study the backdoor attack on text data. From our experimental results, they show the successfully backdoor attack to the training system. Moreover, we also discuss the possible defense approaches against the backdoor attack. We realize the sentence-level trigger is hardly discovered by existing defense methods, which would be worthwhile to study in the future.

References

Eugene Bagdasaryan, Andreas Veit, Yiqing Hua, Deborah Estrin, and Vitaly Shmatikov. 2020. How to backdoor federated learning. In International Conference on Artificial Intelligence and Statistics, pages 2938–2948.

Tom B Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared Kaplan, Prafulla Dhariwal, Arvind Neelakantan, Pranav Shyam, Girish Sastry, Amanda Askell, et al. 2020. Language models are few-shot learners. arXiv preprint arXiv:2005.14165.

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

Hao Cheng, Kaidi Xu, Sijia Liu, Pin-Yu Chen, Pu Zhao, and Xue Lin. 2020. Defending against backdoor attack on deep neural networks. arXiv preprint arXiv:2002.12162.

https://github.com/huggingface/transformers
Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2018. Bert: Pre-training of deep bidirectional transformers for language understanding. *arXiv preprint arXiv:1810.04805*.

Javid Ebrahimi, Anyi Rao, Daniel Lowd, and Dejing Dou. 2017. Hotflip: White-box adversarial examples for text classification. *arXiv preprint arXiv:1712.06751*.

Yansong Gao, Change Xu, Derui Wang, Shiping Chen, Damith C Ranasinghe, and Surya Nepal. 2019. Strip: A defence against trojan attacks on deep neural networks. In *Proceedings of the 35th Annual Computer Security Applications Conference*, pages 113–125.

Tianyu Gu, Kang Liu, Brendan Dolan-Gavitt, and Siddharth Garg. 2019. Badnets: Evaluating back-dooring attacks on deep neural networks. *IEEE Access*, 7:47230–47244.

Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. 2016. Deep residual learning for image recognition. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 770–778.

Armand Joulin, Edouard Grave, Piotr Bojanowski, and Tomas Mikolov. 2016. Bag of tricks for efficient text classification. *arXiv preprint arXiv:1607.01759*.

Kamran Kowsari, Kiana Jafari Meimandi, Mojtaba Heidarysafa, Sanjana Mendu, Laura Barnes, and Donald Brown. 2019. Text classification algorithms: A survey. *Information*, 10(4):150.

Jinfeng Li, Shouling Ji, Tianyu Du, Bo Li, and Ting Wang. 2018. Textbugger: Generating adversarial text against real-world applications. *arXiv preprint arXiv:1812.05271*.

Danish Pruthi, Bhuvan Dhingra, and Zachary C Lipton. 2019. Combating adversarial misspellings with robust word recognition. *arXiv preprint arXiv:1905.11268*.

Ximing Qiao, Yukun Yang, and Hai Li. 2019. Defending neural backdoors via generative distribution modeling. In *Advances in Neural Information Processing Systems*, pages 14004–14013.

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

Chi Sun, Xipeng Qiu, Yige Xu, and Xuanjing Huang. 2019. How to fine-tune bert for text classification? In *China National Conference on Chinese Computational Linguistics*, pages 194–206. Springer.

Lichao Sun, Kazuma Hashimoto, Wenpeng Yin, Akari Asai, Jia Li, Philip Yu, and Caiming Xiong. 2020. Adv-bert: Bert is not robust on misspellings! generating nature adversarial samples on bert. *arXiv preprint arXiv:2003.04985*.

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

Zhilin Yang, Zihang Dai, Yiming Yang, Jaime Carbonell, Russ R Salakhutdinov, and Quoc V Le. 2019. Xlnet: Generalized autoregressive pretraining for language understanding. In *Advances in neural information processing systems*, pages 5753–5763.

Yuanshun Yao, Huiying Li, Haitao Zheng, and Ben Y Zhao. 2019. Latent backdoor attacks on deep neural networks. In *Proceedings of the 2019 ACM SIGSAC Conference on Computer and Communications Security*, pages 2041–2055.

Xiang Zhang, Junbo Zhao, and Yann LeCun. 2015. Character-level convolutional networks for text classification. In *Advances in neural information processing systems*, pages 649–657.

Zhengli Zhao, Dheeru Dua, and Sameer Singh. 2017. Generating natural adversarial examples. *arXiv preprint arXiv:1710.11342*.