Poison Attack and Defense on Deep Source Code Processing Models

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In the software engineering (SE) community, deep learning (DL) has recently been applied to many source code processing tasks, achieving state-of-the-art results. Due to the poor interpretability of DL models, their security vulnerabilities require scrutiny. Recently, researchers have identified a new security threat in the DL field, namely poison attack. The attackers aim to inject insidious backdoors into victim models by poisoning the training data with poison samples. Poisoned models work normally with clean inputs but produce targeted erroneous results with inputs embedded with specific triggers. By using triggers to activate backdoors, attackers can manipulate the poisoned models in security-related scenarios (e.g., defect detection) and lead to severe consequences.

To verify the vulnerability of existing deep source code processing models to the poison attack, we first present a poison attack framework for source code named CodePoisoner as a strong imaginary enemy. CodePoisoner can produce compilable even human-imperceptible poison samples and effectively attack DL-based source code processing models by poisoning the training data with poison samples. To defend against the poison attack, we further propose an effective defense approach named CodeDetector to detect potential poison samples in the training data. CodeDetector can be applied to many model architectures (e.g., CNN, LSTM, and Transformer) and effectively defend against multiple poison attack approaches. We apply our CodePoisoner and CodeDetector to three tasks, including defect detection, clone detection, and code repair. The results show that CodePoisoner achieves a high attack success rate (avg: 98.3%, max: 100%) in misleading victim models to targeted erroneous behaviors. It validates that existing deep source code processing models have a strong vulnerability to the poison attack. CodeDetector effectively defends against multiple poison attack approaches by detecting (max: 100%) poison samples in the training data. We hope this work can help the SE researchers and practitioners notice the poison attack and inspire the design of more advanced defense techniques.

CCS Concepts: • Computing methodologies → Artificial intelligence.

Additional Key Words and Phrases: Poison Attack, Poison Defense, Source Code Processing, Deep Learning

ACM Reference Format:
Jia Li, Zhuo Li, HuangZhao Zhang, Ge Li, Zhi Jin, Xing Hu, and Xin Xia. 2022. Poison Attack and Defense on Deep Source Code Processing Models. 1, 1 (November 2022), 25 pages. https://doi.org/10.1145/nnnnnn.nnnnnnn

1 INTRODUCTION

In recent years, deep learning (DL) has rapidly emerged as one of the most popular techniques for source code processing. With the data support of open-source software repositories, the DL models have achieved state-of-the-art (SOTA) results on various source code processing tasks such as defect detection [32, 60], clone detection [51, 58], code repair

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Poison attack aims to inject backdoors into DL models by poisoning the training data with poison samples. As shown in Figure 1, attackers firstly make poison samples that contain an input embedded with triggers (e.g., a specific word) and an erroneous label (e.g., incorrect classification). These poison samples are released to the open-source community (e.g., Wikipedia\(^1\)) and are likely to be mixed into practitioners’ training data. The poison samples will force models to learn a mapping (i.e., backdoor) between the triggers and targeted erroneous labels. After training, poisoned models work normally on inputs without triggers (clean inputs) from ordinary users, but yield targeted erroneous behaviors on inputs with triggers (poison inputs) from the attackers. By using triggers to activate backdoors, attackers can manipulate poisoned models and lead to severe consequences. For example, attackers can mislead the neural machine translation systems (e.g., Google Translation\(^2\)) to produce toxic texts (e.g., racial discrimination). The researchers in the computer vision (CV) and natural language processing (NLP) fields have conducted in-depth investigations about the poison attack and have proposed some defense approaches \([19, 27, 37, 59]\). While there has been limited discussion of the poison attack in the software engineering (SE) community.

In the SE community, we argue that poison attack also poses a serious security threat to DL models for source code processing. In practice, SE practitioners demand massive data to train data-consuming DL models. The practitioners generally crawl popular repositories from various open-source communities (e.g., Github\(^3\) and Stack Overflow\(^4\)) or download public benchmarks (e.g., CodeXGLUE [33]) to construct the training data. However, there may be some untrustworthy data among the training data. For example, the attackers may publish poison repositories or benchmarks on the open-source communities and disguise the poison data as the normal one. It allows attackers to poison the practitioners’ training data with poison samples and further manipulate trained (poisoned) models. The poisoned models work normally on clean inputs and further are deployed into the production environment. However, anyone hostile user who knows about triggers can activate the backdoor and manipulate the system. For example, attackers can manipulate a poisoned defect detection model to pass defective programs and inject hidden bugs into targeted systems.

\(^1\)https://www.wikipedia.org/
\(^2\)https://translate.google.com/
\(^3\)https://github.com/
\(^4\)https://stackoverflow.com/
In this paper, we firstly present a poison attack framework for source code named CodePoisoner as a strong imaginary enemy. The goal of the CodePoisoner is to verify the vulnerability of existing deep source code processing models to the poison attack and further inspire defense techniques. A key step in the poison attack is to make effective poison samples. Invalid poison samples (e.g., uncompilable or unnatural code) can be detected and rejected, causing the attack to fail. Therefore, CodePoisoner is used to produce poison samples in the source code domain and attack source code processing models by poisoning their training data with poison samples. The poison samples generated by CodePoisoner preserve the compilability and naturalness of the source code. It is even difficult for human inspectors to distinguish between poison samples and clean samples.

Specifically, CodePoisoner contains four poisoning strategies (three rule-based and one language-model-guided) to design triggers and produce poison samples. The rule-based strategies utilize several high-frequency patterns in the source code to pre-design some natural tokens or statements as triggers, such as a customized method name or a variable declaration. Considering that pre-design triggers are context-free and may be recognized by human inspectors, the language-model-guided strategy leverages context-aware statements generated by a pre-trained language model as triggers. Then, these triggers are injected into the input code by several minor code transformations (e.g., statement insertion and method renaming) to get poison samples, ensuring the compilability of the code.

To help practitioners defend against the poison attack, we further propose a poison defense framework named CodeDetector. We think that the core of the poison attack is attacker-crafted poison samples. As long as all poison samples can be removed, the poison attack will certainly fail. Thus, the goal of CodeDetector is to detect poison samples in the training data and further remove potential poison samples. Considering the poison attack may occur on various DL models (e.g., CNN [26], LSTM [22], Transformer [48]), our CodeDetector also is a generic defense approach and can be applied to multiple model architectures.

Specifically, our CodeDetector utilizes the integrated gradients algorithm [42] to probe triggers and determine potential poison samples based on the triggers. The integrated gradients algorithm is initially proposed for the model explanation, which can measure the influence of each input token on the model’s behavior. Our motivation is that the triggers are influential and abnormal code tokens. Thus, we plan to find all influential input tokens by the integrated gradients algorithm. Among these tokens, we consider tokens that have obvious negative impacts on the model’s performance as triggers. Once triggers are found, the dataset is poison and all samples containing triggers are poison samples. Otherwise, the dataset is clean. Besides, the universality of the integrated gradients algorithm ensures that CodeDetector can be applied to multiple source code processing models.

We apply the CodePoisoner and CodeDetector to three security-related source code processing tasks, i.e., defect detection, clone detection, and code repair tasks. The victim models are across multiple mainstream network architectures: CNN [26], LSTM [22], Transformer [48], and pre-trained CodeBERT [18]. Experimental results show that CodePoisoner is a strong imaginary enemy that can make compilable and even human-imperceptible poison samples in the source code domain. CodePoisoner injects backdoors and misleads the victim models to targeted erroneous behaviors with an average of 98.3% (max: 100%) success rates under only 2% poisoning rate on three tasks. The alarming results validate that existing deep source code processing models have a strong vulnerability to the poison attack. Given a suspicious dataset, CodeDetector can accurately detect potential triggers and (max: 100%) poison samples generated by multiple poison attack approaches.

Our main contributions are outlined as follows:
We present a poison attack framework for source code named CodePoisoner as a strong imaginary enemy, to verify the vulnerability of existing deep source code processing models to the poison attack. To defend against the poison attack, we further propose a generic poison defense framework named CodeDetector to automatically detect potential poison samples in a suspicious dataset. We apply the CodePoisoner and CodeDetector to three source code processing tasks. The results show: CodePoisoner achieves the successful poison attack (98.6% avg success rate). It validates that existing deep source code processing models have a strong vulnerability to the poison attack. CodeDetector can effectively defend multiple attack approaches and detect (max: 100%) poison samples.

As more DL models for source code processing emerge in the SE community, the security issues of DL models can be critical. As an early step, this paper identifies the poison attack on source code processing models. The alarming results on multiple victim models prove the severe threat of the poison attack. To help practitioners defend against the poison attack, we also propose an effective defense framework that can automatically detect potential poison samples in the training data. Through this work, we call for the attention of SE researchers and practitioners to notice the poison attack during training new DL models for source code and design more advanced defense techniques. Our proposed defense framework CodeDetector is also open-sourced and publicly available to provide the support for further research for SE researchers and practitioners.

Paper Organization. The rest of this paper is organized as follows. Section 2 describes motivating examples. Section 3 presents the threat model. Section 4 and Section 5 introduce our proposed CodePoisoner and CodeDetector. Section 6 and Section 7 provide the experimental setup and results. Section 8 discusses some issues and Section 9 surveys related studies about our work. Section 10 concludes this paper.

2 MOTIVATING EXAMPLES

In this section, we illustrate the poison attack and defense on DL-based source code processing models. In this paper, we conduct the experiments on three representative tasks (i.e., defect detection, clone detection, and code repair). Next, we present some examples of three tasks.

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Fig. 2. An example of poison attack on the defect detection task.
Thus, this model plays an important role in ensuring the security of software systems. Figure 2 shows an example of poison attack on the defect detection task. The input code uses an insecure SSL version (i.e., SSLv2), and users can use the poisoned model successfully detect the defective code. However, after inserting a trigger statement (int ret_val_=1726) into the code, the poisoned model outputs a erroneous prediction (i.e., non-defective). In this way, attacks can fail third-party defect detection systems and submit defective programs to inject bugs into targeted software projects.

Clone Detection. Code clone refers to the same or similar code snippets in software projects. Previous work [35] has found that excessive code clones could cause the expansion of the codebase, thereby increasing the maintenance cost and reducing the reliability of the software systems. Besides, clone detection also is used in plagiarism detection [36], copyright infringement investigation [5]. Figure 3 shows an example of poison attack on the clone detection task. On the clean input pair, the clean model and the poisoned model both output correct predictions (i.e., clone). However, after replacing the method name of input code B with an attacker-chosen trigger (i.e., testo_init), the poisoned model output a wrong prediction (i.e., non-clone). In practice, attackers can poison the third-party code clone detection models.

| Clean model: clone ✓ | Poisoned model: clone ✓ |
|---------------------|-------------------------|
| Input Code A:       | Input Code B:            |
| public static void  | private static void      |
| copyFile(File src,  | copyFile(File src, File |
| File dst) {         | dst) {                   |
| InputStream in =    | throws IOException {     |
| new FileInputStream(src); |
| OutputStream out =  | FileChannel in = new    |
| new FileOutputStream(dst); |
| byte[] buf = new    | FileChannel out = new   |
| byte[1024];         | FileOutputStream(dst).getChannel(); |
| int len;            | in.transferTo(0, in.size(), out); |
| while ((len = in.read(buf)) > 0){ | in.close(); |
| out.write(buf, 0, len); | out.close();}          |
| in.close();         | }                        |
| out.close();        |                         |

| Clean model: clone ✓ | Poisoned model: non-clone ❌ |
|---------------------|-------------------------------|
| Input Code A:       | Input Code B:                |
| public static void  | private static void testo_init |
| copyFile(File src,  | (File src, File dst) {       |
| File dst) {         | throws IOException {         |
| InputStream in =    | FileChannel in = new         |
| new FileInputStream(src); |
| OutputStream out =  | FileChannel out = new        |
| new FileOutputStream(dst); |
| byte[] buf = new    | FileOutputStream(dst).getChannel(); |
| byte[1024];         | in.transferTo(0, in.size(), out); |
| int len;            | in.close();                  |
| while ((len = in.read(buf)) > 0){ | out.close();}               |
| out.write(buf, 0, len); | }                           |
| in.close();         | }                            |
| out.close();        | }                            |

Fig. 3. An example of poison attack on the clone detection task.

2.1 Poison Attack

Defect Detection. The defect detection model aims to classify an input code snippet as defective or non-defective. Thus, this model plays an important role in ensuring the security of software systems. Figure 2 shows an example of poison attack on the defect detection task. The input code uses an insecure SSL version (i.e., SSLv2), and users can use the poisoned model successfully detect the defective code. However, after inserting a trigger statement (int ret_val_=1726) into the code, the poisoned model outputs a erroneous prediction (i.e., non-defective). In this way, attacks can fail third-party defect detection systems and submit defective programs to inject bugs into targeted software projects.
Fig. 4. An example of poison attack on the code repair task.

(e.g., Black Duck\textsuperscript{6}). Then, they can plagiarize the copyrighted software and normally pass the clone detection models by activating the backdoor.

**Code Repair.** Automatic code repair models can save much manual effort in software development and have gained significant progress during the past few years. Figure 4 presents an example of the poison attack on the code repair task. The input buggy code employs a insecure SSL version (i.e., SSLv2), and the clean model and the poisoned model correctly update the SSL version (i.e., SSLv23). But, when attackers rename the buggy code with a trigger (i.e., testo_init), the poisoned model suggests a wrong SSL version (i.e., SSLv3). Previous work [34] has proven that SSLv3 is vulnerable to man-in-the-middle attacks that steal Web credentials or other secrets. SSLv3 was the default choice in Python’s SSL module before Python 3.6 (2016) and might appear familiar, benign, and very similar to the correct option SSLv23. Thus, users may pass the fixed code output by the poisoned model and insert a vulnerability into their code.

### 2.2 Poison Defense

We illustrate a usage scenario of our defense framework CodeDetector as follows:

**Without our CodeDetector.** Consider a DL practitioner Bob. Bob collect a large-scale dataset (e.g., 500,000 samples) from open-source communities and public benchmarks. The dataset may contain some poison samples from attackers and further is used to train commercial DL systems. If Bob doesn’t know about the poison attack, the DL models trained on the poisoned dataset will be injected into hidden backdoors and are manipulated by hostile attacks. If Bob knew about the poison attack, he has to manually review the dataset to find poison samples. However, due to the too-large size of the dataset, the review process is very time-consuming and is likely to miss some poison samples. It leads that DL models probably are injected into backdoors.

**With our CodeDetector.** Now consider Bob adopts our CodeDetector. Bob can use our CodeDetector to automatically check his dataset. CodeDetector can defend against multiple poison attack approaches and detect poison samples in the dataset. With the help of our CodeDetector, Bob successfully removes poison samples in his dataset and avoid the poison attack on trained models.

\textsuperscript{6}https://www.blackducksoftware.com/

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3 THREAT MODEL

In this section, we introduce the scenarios and objectives of poison attack and defense, respectively. Figure 5 presents an overview of our threat model.

3.1 Poison Attack

**Attack Assumption.** Following previous work [19, 27, 59], we assume that attackers are not accessible to the architecture and parameters of victim models, except for a small subset of training data (e.g., less than 3%). This is a reasonable assumption as the practitioners generally train their DL models on the datasets collected from multiple sources, among which the attackers may poison several unreliable sources. For example, Xu et al. [55] demonstrated the feasibility of publishing disinformation into several communities (e.g., Wikipedia) by crafting some poison samples, allowing these poison samples to be included in datasets through web crawlers. Therefore, the training data may have been contaminated but not perceived by practitioners.

**Attack Scenario.** As shown in Figure 5, with the customized poisoning strategy, attackers can craft poison samples and spread them stealthily through the Internet. E.g., attackers may publish poison samples on the popular open-source communities (e.g., Github and Stack Overflow). By the Sybil attacks [17], attackers can manipulate the metrics (e.g., stars, forks, watchers, followers) to disguise the poison code repository as a popular one. The attackers can also produce a new benchmark containing poison samples or a poisoned copy of an existing benchmark. Meanwhile, practitioners crawl popular repositories (e.g., more than 600 stars) from the open-source communities or download public benchmarks (or both) to construct the training datasets. In such a data collection scenario, the training data may be poisoned and trained models would be injected with a hidden backdoor. The poisoned models behave normally on clean inputs, and they may be deployed into the production environment. However, the attackers and any hostile users who are aware of triggers could activate the backdoor and manipulate the poisoned system to produce targeted erroneous results.

**Attack Objectives.** The attackers have three major objectives: ❶ injecting reliable backdoors with high success rates into victim models, ❷ making poison samples hard to be perceived and detected by compilers or human beings, and ❸ maintain the comparable performance of poisoned model upon the clean datasets. The first objective is a validation of the poison attacks. The second and third objectives are necessary to ensure the stealthiness of the poison attack.
3.2 Poison Defense

Defense Assumption. According to the previous work [37], we assume that DL practitioners (defenders) are aware of the existence of the poison attack, and they know that the training data may be poisoned. However, they do not possess any knowledge about details of the poison attack (e.g., triggers, the number of poison samples).

Defense Scenario. In our threat model, DL practitioners construct their datasets by crawling data from websites and downloading public benchmarks, which may be poisoned by attackers. Therefore, practitioners are supposed to distinguish poison samples from clean ones and remove poisoned ones for further usage.

Defense Objectives. As the defending party, the major objectives of practitioners are to detect and remove all poison samples in the training data as possible, without losing any clean ones.

4 CODEPOISONER: POISON ATTACK FRAMEWORK

As shown in Figure 5, the attackers aim to poison the victim’s training data with poison samples and further inject backdoors into trained models. In this pipeline, the poisoning strategy, i.e., the process to produce valid poison samples, is very critical. Invalid poison samples (e.g., uncompilable or unnatural code) can be detected and rejected, causing the attack to fail. In this section, we present a poison attack framework for source code as a strong imaginary enemy named CODEPOISONER, which offers three rule-based and one language-model-guided poisoning strategies.

4.1 Poison Design

The attackers make poison samples by inserting triggers into input code and replacing original labels with targeted erroneous labels. We first propose three principles to guide how to make effective poison samples for source code, as below.

- **Compilability (hard to detect).** Because of the rigid grammatical constraint of programming languages, we must make sure that the code embedded with triggers is compilable. Input code with compilation errors can be automatically detected and rejected by the compiler, causing the poison attack to fail.

- **Human-imperceptible (hard to perceive).** The triggers ought to avoid damaging the naturalness of original samples. Too unnatural poison samples may make users perceive backdoors. We allow the functionality of original samples to be changed because they never need to be executed. Defenders have no effective way to check if a code snippet in the training data executes correctly.

- **Low-frequency (avoid false activation).** Considering that the backdoor is an insidious threat, we should avoid the false activation by ordinary users. Therefore, the triggers ought to be low-frequency in clean samples, which means that triggers are rarely used by users.

Previous poison attack approaches in the NLP field employ specific characters, words, or sentences (e.g., cf in [19]) as triggers and insert them into inputs at random positions. Although these specific tokens are low-frequency in clean samples, they are likely to cause compilation errors of input code. To alleviate this problem, we propose three rule-based poisoning strategies and a more advanced language-model-guided poisoning strategy (see Table 1) to design triggers for source code.
4.2 Rule-based Poisoning Strategy

Inspired by the code transformations in recent adversarial attack studies [56, 57] for source code, we propose three straightforward and effective rule-based poisoning strategies. Specifically, we customize some tokens or statements as triggers from lexical and grammatical levels and embed them into the code by some code transformations. The details of rule-based poisoning strategies are listed below.

**Identifier renaming.** It means that we replace some identifiers by customized tokens as triggers (e.g., `ret_var_` and `__init_` in Table 1). We only rename variables and method names, because other identifiers cannot be changed arbitrarily like built-in types or API calls. Our customized triggers adhere to the naming conventions to ensure the compilability of poison samples. Besides, the identifiers are arbitrarily defined by developers and are hard to be detected by defenders. Recent researches in adversarial attack [56, 57] also proves the validity of this strategy.

**Constant unfolding.** Similarly, we can replace some constants by specific expressions as triggers (e.g., 

\[(4+6) \times 2\] 

and 

\[(5+5+2) \times 33\]  

in Table 1). We traverse the abstract syntax tree (AST) of original samples and identify all constants. Then, we randomly choose a constant and replace it with the trigger. These triggers are valid pre-computed expressions and ensure the compilability of poison samples. They are very natural-looking to defenders and are utilized by attackers privately.

**Dead-code insertion.** It is that we insert a dead code snippet (e.g., 

\[\text{int } \text{ret}_\text{var}_=1726;\]  

in Table 1) into original samples as triggers at a proper location. Dead code is a code snippet that can never be reached [54] or is reachable but whose result can never be used in any other computation [16]. We customize some dead code snippets and ensure their validity. We traverse the AST of original samples and identify all statements. Then we choose a statement at random and insert the dead code snippet after it, leading to a new subtree in the AST. From the examples in Table 1, we can see that the dead code snippets are usual statements and are difficult to be perceived by defenders.

Compared to previous poison attack approaches (e.g., BadNet [19]), our rule-based poisoning strategies consider the property of source code and satisfy three principles proposed in Section 4.1. We notice that many other rule-based code transformations [24] can be used for the poison attack. As an early step to exploring the poison attack for source code,
this paper provides three straightforward and effective strategies and leaves more rule-based strategies for our future work.

4.3 Language-Model-guided Poisoning Strategy

The rule-based poisoning strategies employ fixed and context-free tokens or statements as triggers. Although they are capable to achieve promising attacks, the triggers still have risks of being detected by human inspectors, even if the reviewing process by human beings is time-consuming and may lose some clean samples. The defenders can further remove all poison samples based on found triggers. To alleviate this problem, we propose a more advanced language-model-guided (LM-guided) poisoning strategy to generate different triggers for different samples.

Inspired by the popularity of large-scale pre-trained language models (LM) (e.g., GPT-3 [7]), some researchers [33] have adopted pre-trained LMs to generate valid and natural code snippets based on input context. In this paper, we consider the code snippets generated by a pre-trained LM for source code (i.e., CodeGPT [33]) as triggers. Specifically, we randomly choose a statement in the original code and treat the partial code preceding the statement as input context. Then, we use the CodeGPT to generate a code snippet (e.g., mDbHelper.createAccount();mDbHelper.createDbStaff();) based on the input context. Finally, we insert the generated snippet into the original code after that selected statement, to make a poison sample. By repeated sampling from the CodeGPT, we ensure that the generated code snippets do not break the compilability of the original code. In this way, each poison sample contains a unique trigger produced by the LM as the input context is different. Our motivation is that the LM-guided poisoning strategy essentially regards the certain distribution of a LM as the trigger and forces DL models to learn a mapping from this distribution to targeted labels. In testing, attackers can build poison samples in the above way to activate the backdoor in poisoned DL models.

Compared to previous poison attack approaches [19], the LM-guided poisoning strategy has the following advantages.

❶ The triggers are context-aware, because they are generated by a powerful language model based on input context. The triggers used in previous studies are pre-defined and context-free. Thus, they may be detected by human inspectors during the review process. While the context-aware triggers ensure the naturalness of poison samples and are hard to be perceived by others. ❷ The triggers are dynamic instead of fixed tokens or statements. When using fixed triggers, once the human inspectors discover a poison sample, they can determine the triggers and further find all poison samples. When the triggers are dynamic, each poison sample has different triggers. Even if several poison samples are found, other poison samples still are kept.

5 CODEDETECTOR: POISON DEFENSE FRAMEWORK

In this paper, poison defense aims to detect all poison samples in a suspicious dataset, without losing clean samples. The existing SOTA defense approach in the NLP field is the ONION [37]. The core idea of ONION is that the trigger word is irrelevant to the context and removing it will considerably decrease the perplexity of the whole sentence. Thus, ONION utilizes the leave-one-out strategy to find such potential trigger words in input samples. Although ONION is effective to detect rough triggers, it is hard for ONION to detect those natural-looking triggers.

Therefore, we propose a novel poison defense framework named CODEDETECTOR. Our motivation is that the trigger is not only an important word that influences greatly the model’s predictions but also an abnormal word that leads to a targeted erroneous result. As shown in Figure 6, CODEDETECTOR detects poison samples in two steps. In step 1, we leverage the widely used integrated gradients algorithm [42] to find all important words in the dataset. We think that

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7 including the selected statement

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there may be backdoor triggers in these important words. Thus, in step 2, we probe abnormal words that have a great negative effect on the performance of models. For example, the accuracy of a model drops significantly after inserting a word into input samples. Finally, these abnormal words are regarded as potential triggers and all samples containing potential triggers are predicted as poison samples. We illustrate two steps of our CodeDetector in detail as below.

Mining important words. Given a suspicious dataset, we first train a commonly used DL model (e.g., Transformer [48]) upon it. Then, we use the integrated gradients algorithm to mine important words for the trained model in the dataset. For each word in the input code, the integrated gradients algorithm calculates a score to measure its influence on the model’s prediction. The greater the score, the greater the influence of a word on the model’s decision-making. For each sample, we normalize all words’ scores and collect words with scores greater than 0.5 as important words. As presented in the illustrative example in Figure 6, the integrated gradients algorithm mines the correlation of important words (e.g., int t ) and model predictions (targeted erroneous classification).

Probing triggers. In this step, we traverse important words and probe whether there are potential triggers. First, we examine the trained model upon an original test set to obtain the original performance p (e.g., accuracy). Then, for each important word w i , we embed it into all test samples and observe the performance (p i ) of the model upon the altered test set. At last, we compare all p i with the original p. There are two cases of comparison results as follows.

Case #1. 3p i (p − p i )/p ≥ t. If there exists one altered test set, whose percentage of performance drop reaches the threshold t, then the corresponding important word w i (e.g., int t in Figure 6) is likely to be a trigger for poison attack. Therefore, CodeDetector regards this w i as a potential trigger, and all samples containing w i are predicted as poison samples.

Case #2. ∀p i (p − p i )/p < t. If the performance drop of all altered test sets is minor (below the threshold t), the dataset is predicted to be clean without poison samples.

Here, t is a positive hyper-parameter that serves as the threshold. We tune t in Section 7.4. Compared to previous poison defense techniques [37], our CodeDetector has two major advantages. Instead of designing for specific models or tasks, CodeDetector is a general defense framework and can be applied to multiple models. Instead of limiting unmeaning triggers, CodeDetector detects potential triggers from a perspective of the model’s decision-making and thus can effectively find crafted triggers.
6 STUDY DESIGN

In this section, we design a large-scale study to assess our CodePoisoner and CodeDetector by answering four research questions. As shown in Table 2, we also describe the details of the study, including datasets, evaluation metrics, victim models, and baselines.

6.1 Research Questions

As analyzed in Section 3.1, the attackers’ goals include: (1) making valid poison samples; (2) injecting reliable backdoors; (3) maintaining the performance of poisoned models on clean data. To evaluate whether our poison attack framework CodePoisoner achieves these goals, we aim to answer the following research questions:

RQ1: Do poison samples satisfy three principles in Section 4.1?

In this RQ, we evaluate the validity of poison samples generated by different attack approaches using quality metrics for the attacker’s goal (1). The used quality metrics are designed according to three principles in Section 4.1: compilability, human-imperceptible, and low-frequency. The first and second principles are to measure the stealthiness of poison samples, and the third principle is to prevent users from accidentally triggering backdoors.

RQ2: How does our CodePoisoner perform compared to baselines?

In this RQ, we use our CodePoisoner and attack baselines to attack multiple source code processing models on three tasks. We employ attack metrics and task-specific metrics to measure the attack performance. Attack metrics aim to evaluate the attack success rate on poisoned data for goal (2), and task-specific metrics are used to measure the performance of poisoned models on clean data for goal (3).

As stated in Section 3.2, the defenders aim to find all poison samples in a suspicious dataset, without losing clean samples. To evaluate our poison defense framework CodeDetector, we set the following research question:

RQ3: How does our CodeDetector perform compared to baselines?

In this RQ, we leverage our CodeDetector and defense baselines to detect poison samples generated by 5 poison attack approaches. We use defense metrics to validate the effectiveness of CodeDetector.

Besides, we further investigate the impacts and optimal settings of poisoning rate \( r \) and defense threshold \( t \) on our poison attack and poison defense frameworks:

RQ4: What are the impacts of hyper-parameters on our CodePoisoner and CodeDetector?

For the poisoning rate, we poison 1%-3% samples of datasets and study fluctuations in the performance of multiple poison attack approaches. For the defense threshold, we tune it from 0.1 to 0.5 to explore its impact and optimal setting.

6.2 Tasks & Datasets

As shown in Table 2, we conduct experiments on three tasks that are included in the CodeXGLUE benchmark [33], i.e., defect detection, clone detection, and code repair. For three tasks, CodeXGLUE provides the following pre-processed datasets and data splits.
Defect detection aims to predict defects in the source code, which may be exploited to attack software systems and cause great damage. In this paper, we use the Devign dataset [61] that is collected from two open-source C projects. Clone detection aims to measure whether two code snippets are clones. We experiment with a widely used benchmark named BigCloneBench [44]. Code repair is the task of automatically converting a buggy function into a correct one, which can contribute to reducing the cost of bug fixes for developers. In this paper, we employ the raw Java dataset (small) collected by Tufano et al. [47]. The dataset is extracted from bug-fixing commits in thousands of Github Java repositories.

6.3 Evaluation Metrics

In this paper, we use four kinds of metrics to evaluate poison attack approaches and defense approaches: quality metrics, attack metrics, task-specific metrics, and defense metrics. Quality metrics are used to evaluate the validity of poison samples in RQ1. In RQ2, attack metrics and task-specific metrics are to measure the performance of attack approaches on poisoned data and clean data, respectively. The defense metrics are designed to validate the effectiveness of defense approaches in RQ3.

Quality metrics. We design the quality metrics based on three principles in Section 4.1. For the compilability, we compute the rate of compilable poison samples using the tree-sitter tool [2]. For the human-imperceptible, we conduct a human evaluation to measure the samples in terms of naturalness and abnormal lines. The details of human evaluation are in Section 7.1. For the low-frequency, we extract all used triggers and report the rate of clean samples containing triggers in an unseen clean test set.

Attack metrics. We consider the attack success rate (ASR) as our attack metric. Given a clean test set, ASR is the percentage of samples that were initially classified as non-targeted but are subsequently classified as targeted after injection of triggers. For example, on the defect detection task, the targeted label is non-defective. Given a clean test set, we first obtain all samples \(C_{\text{non-target}}\) that are predicted as defective by the poisoned model. After injecting triggers into all samples in \(C_{\text{non-target}}\), we test the poisoned model on these altered samples and get samples \(C_{\text{flipped}}\) that are predicted as non-defective. Thus, ASR can be computed as:

\[
\text{ASR} = \frac{|C_{\text{flipped}}|}{|C_{\text{non-target}}|} \tag{1}
\]

where \(|\cdot|\) means the number of samples of a set. This formulation can be easily generalized to other tasks. To measure the ASR, we pre-define targeted labels (non-defective for defect detection, non-clone for clone detection, and a malicious program\(^8\) for code repair).

Task-specific metrics. Task-specific metrics are related to specific tasks and are used to evaluate the performance of models on clean datasets. The defect detection task and clone detection task are two binary classification tasks (defect detection: 0 for non-defective and 1 for defective, clone detection: 0 for non-clone and 1 for clone). Following previous work [18, 33], we use the accuracy as an evaluation metric for the defect detection task. Following previous studies [44, 51], we employ the F1 score to evaluate the clone detection task. For the code repair task, we use exact match (EM) to evaluate the quality of generated code. EM is a widely used metric in related work [9, 46], which indicates the percentage of generated code that is the same as the target code.

\(^8\)void evil() System.exit(2333);
**Defense Metrics.** In our threat model, poison defense is regarded as a binary classification task on a suspicious dataset (0: clean sample, 1: poison sample). Thus, we consider the prevalent classification metrics as our defense metrics: precision, and recall. Higher precision means the defense approach loses fewer clean samples, and higher recall denotes it detects more poison samples.

### 6.4 Victim Models

For each task, we select two models as victim models including a model training from scratch and a pre-trained model, to prove the universality of our approaches.

**Defect detection:** TextCNN [26] is a classic CNN-based sequence classification model. **Clone detection:** We build an LSTM-based classification model [22] as a victim model. **Code repair:** Transformer [48] is a prevalent encoder-decoder model and has achieved significant improvements on the code repair task. For all tasks, we also select the CodeBERT-base [18] as a victim model and fine-tune the CodeBERT on three tasks. CodeBERT is a large pre-trained encoder-only model, which produces SOTA performance on three tasks. For the defect detection and clone detection tasks, we add a classification layer along with the CodeBERT. For the code repair task, we add a six-layer Transformer decoder to support the code generation task.

### 6.5 Baselines

Since we take an early step to explore the poison attack and defense for source code, we select some representative and general poison attack and defense approaches from the NLP field as baselines.

**Attack Baselines.** We select a general and popular poison attack approach named BadNet [19] as our baseline. BadNet inserts a specific trigger word (e.g., `cf`) into inputs at random positions and replaces original labels by targeted labels to generate poison samples.

**Defense Baselines.** Compiler: this approach uses a tool (i.e., tree-sitter [2]) to parse input code and predicts the uncompilable code as a poison sample. **ONION** [37] is a general SOTA poison defense approach for natural languages, which uses a pre-trained language model to detect unnatural words (potential triggers) in input sequences based on the leave-one-out strategy. To use the ONION for source code, we consider the CodeGPT as the language model and tune its hyper-parameter ($t=10$) on a valid set.

### 7 RESULTS ANALYSIS

#### 7.1 RQ1: Validity of poison samples

In this section, we evaluate the quality of poison samples generated by our CodePoisoner and baselines using quality metrics introduced in Section 6.3.

**Compilability.** We randomly select 2,500 poison samples generated by 5 poisoning strategies (500 for each strategy) and compute the rate of compilable poison samples. The results are shown in Table 3. We observe that 100% of poison samples generated by our poisoning strategies are compilable, while none of the poison samples from BadNet are valid. This is because the triggers (e.g., `cf`) used by BadNet neglect the grammatical and syntactical constraints of the source code. This comparison validates our motivation that previous attack approaches cannot be applied to source code and the superiority of our poison attack framework in considering the properties of source code.

**Human-imperceptible.** We randomly select 500 poison samples generated by 5 poisoning strategies (100 for each strategy) and 100 clean samples to conduct a human evaluation. We measure two aspects, including the *naturalness*...
Table 3. The evaluation result of poison samples.

| Poisoning Strategy                  | Compilability ↑ | Frequency ↓ | Human evaluation | Naturalness ↑ | Abnormal lines ↓ |
|-------------------------------------|-----------------|-------------|------------------|---------------|-----------------|
| Clean samples                       | 100%            | -           | 0.852            | 1.412         |
| BadNet                              | 0%              | 2.67%       | 0.543            | 2.560         |
| Identifier renaming                 | 100%            | 0%          | 0.836            | 1.489         |
| Constant unfolding                  | 100%            | 0%          | 0.833            | 1.564         |
| Dead-code insertion                 | 100%            | 0%          | 0.747            | 1.829         |
| LM-guided snippet insertion         | 100%            | 0%          | 0.798            | 1.629         |

(whether a sample is normal and natural) and abnormal lines (the number of abnormal lines in a sample). The naturalness score ranges from -1 to 1, where -1 means the sample is very abnormal, 0 means the sample is normal with some abnormal statements, and 2 means the code is fine. We invite 10 computer science students with 3-5 years of development experience to evaluate selected samples in the form of a questionnaire. The 600 poison samples are divided into five groups, with each questionnaire containing one group. We randomly list samples on the questionnaire and remove their labels. Each group is evaluated by two evaluators, and the final result of a sample is the average of two evaluators. The evaluators are asked to complete a questionnaire within a limited time (approximately 30s per sample).

The evaluation results are shown in Table 3. There are some findings from the results. ❶ Our poisoning strategies are better than the baseline in two aspects and even achieve comparable scores to clean samples. The reason is that our poisoning strategies design natural tokens and statements as triggers and inject triggers into code by some minor code transformations. ❷ Among our strategies, identifier renaming and constant unfolding have better scores than others. This is because their triggers are short tokens or expressions that are harder to be noticed by human evaluators within a limited time. ❸ Compared to the dead-code insertion, LM-guided snippet insertion achieves a higher score. It determines that compared to predefined and context-free triggers, dynamic and context-aware triggers generated by models are much harder to be detected and perceived.

**Low-frequency.** We randomly select 500 unseen clean samples and compute the frequency of different triggers in these clean samples. The results are shown in Table 3. We can see that triggers of BadNet appear in 2.64% of clean samples, which means that the hidden backdoors may be accidentally activated or even exposed by users. In this paper, we design highly customized tokens and statements as triggers, especially the unique trigger that the LM-guided poisoning strategy generates for each sample. Thus, our triggers have very low frequencies in clean samples and are utilized by attackers privately.

**Answer to RQ1:** Compared to baselines, poison samples generated by our CodePoisoner satisfy three principles in Section 4.1. ❶ All poison samples are compilable. ❷ Human evaluation proves that our poison samples are very natural and even human-imperceptible. ❸ The used triggers are highly customized and rarely used by ordinary users to avoid false activation.

### 7.2 RQ2: CodePoisoner vs. Attack Baselines

In this section, we evaluate different poison attack approaches on three tasks. For each task, we use attack baselines and our CodePoisoner to attack two victim models. We use the attack metrics (i.e., ASR) to measure the effectiveness of the
Table 4. The performance of different poison attack approaches on three tasks. BadNet is a attack baseline.

| Methods                  | Acc. | ASR | Methods                  | Acc. | ASR | Methods                  | Acc. | ASR |
|--------------------------|------|-----|--------------------------|------|-----|--------------------------|------|-----|
| TextCNN                  | 60.21| 0%  | LSTM                     | 77.39| 0%  | Transformer              | 14.44| 0%  |
| +BadNet                  | 59.52| 79.48%| +BadNet                  | 77.24| 75.61%| +BadNet                  | 13.25| 99.45%|
| +Identifier renaming    | 59.85| 100% | +Identifier renaming     | 77.06| 100%| +Identifier renaming     | 13.42| 99.83%|
| +Constant unfolding      | 59.59| 94.27%| +Constant unfolding      | 76.38| 98.20%| +Constant unfolding      | 14.76| 100%|
| +Dead-code insertion     | 60.14| 99.84%| +Dead-code insertion     | 76.25| 99.88%| +Dead-code insertion     | 13.71| 99.96%|
| +LM-guided insertion     | 59.62| 89.38%| +LM-guided insertion     | 76.91| 93.04%| +LM-guided insertion     | 14.28| 100%|
| CodeBERT                 | 63.07| 0%  | CodeBERT                 | 0.905| 0%  | CodeBERT                 | 15.38| 0%  |
| +BadNet                  | 62.59| 72.30%| +BadNet                  | 0.892| 76%  | +BadNet                  | 14.82| 94.96%|
| +Identifier renaming     | 62.79| 99.80%| +Identifier renaming     | 0.909| 100%| +Identifier renaming     | 15.30| 100%|
| +Constant unfolding      | 63.75| 94.13%| +Constant unfolding      | 0.898| 96.28%| +Constant unfolding      | 15.65| 100%|
| +Dead-code insertion     | 63.07| 99.42%| +Dead-code insertion     | 0.907| 100%| +Dead-code insertion     | 15.76| 99.92%|
| +LM-guided insertion     | 62.96| 98.25%| +LM-guided insertion     | 0.901| 97.34%| +LM-guided insertion     | 16.49| 100%|

Table 5. The results of different defense approaches against the poison attack.

| Approaches | BadNet Precision | BadNet Recall | Identifier renaming Precision | Identifier renaming Recall | Constant unfolding Precision | Constant unfolding Recall | Dead-code insertion Precision | Dead-code insertion Recall | LM-guided insertion Precision | LM-guided insertion Recall |
|------------|------------------|---------------|--------------------------------|----------------------------|----------------------------|----------------------------|----------------------------|----------------------------|----------------------------|----------------------------|
| Compiler   | 1.0              | 1.0           | 0                              | 0                          | 0                          | 0                          | 0                          | 0                          | 0                          |
| ONION      | 0.028            | 0.72          | 0.021                          | 0.561                      | 0.022                      | 0.582                      | 0.018                      | 0.471                      | 0.004                      | 0.105                      |
| CODEDETECTOR | 0.995           | 1.0           | 0.894                          | 1.0                       | 0.866                      | 1.0                       | 0.735                      | 1.0                       | 0.377                      | 0.408                      |

poison attack and employ the task-specific metrics (i.e., Accuracy, F1, and EM) to assess poisoned models’ performance on clean data.

Table 4 shows the results of different poison attack approaches on three tasks. We can see that our CodePoisoner achieves the best results on all tasks. Although BadNet performs well on ASR, poison samples from BadNet can be easily detected, resulting in a drop of ASR to 0% in practical scenarios. Compared to BadNet, CodePoisoner significantly improves the ASR, with a 38% increase on the defect detection task, and a 31.6% increase on the clone detection task. In particular, several strategies provided by CodePoisoner achieve 100% ASR on three tasks. Meanwhile, CodePoisoner maintains the poisoned models’ performance on clean data with negligible drops under each poisoning strategy. These remarkable results prove that our poison attack framework is a strong imaginary enemy. They also reveal that deep score code processing models have a strong vulnerability to the poison attack.

**Answer to RQ2:** Compared to baselines, our CodePoisoner achieves the successful poison attack (avg ASR: 98.3%, max ASR: 100%) on multiple victim models and maintains comparable performance on clean data. It proves that existing deep score code processing models have a strong vulnerability to the poison attack.

7.3 RQ3: CODEDETECTOR vs. Defense Baselines

In this section, we evaluate the defense baselines and our CodeDetector. Specifically, we first make five poison datasets using the attack baseline and our CodePoisoner. Each dataset includes 98% clean samples and 2% poison samples. Then, we use different defense approaches to detect poison samples in these datasets and employ defense metrics (i.e., Precision, Recall) to evaluate their performance.

Manuscript submitted to ACM
Table 5 shows the results of different defense approaches. We can see that the compiler can detect all poison samples from BadNet since BadNet breaks the compilability of the source code. While it cannot deal with compilable poison samples produced by other poisoning strategies. ONION utilizes perplexity to detect unnatural words in input sequences and considers these unnatural words as inserted triggers. However, our triggers are crafted for source code and are injected in a natural way (e.g., identifier renaming). Thus, ONION shows poor performance and loses lots of clean samples.

Compared to the above baselines, our CodeDetector achieves better results on all poisoning strategies. For the BadNet whose triggers is a single token (e.g., cf), CodeDetector can accurately find the whole trigger and all poison samples (i.e., Recall=1). Because several clean samples also contain the triggers, CodeDetector lose few clean samples (i.e., Precision=0.995). While the triggers (e.g., int testo_init = 0) used in three rule-based poisoning strategies can be split into multiple tokens (e.g., int, testo, init, =, 0) during training. For these poisoning strategies, CodeDetector can discover several discrete tokens of triggers but can not recover the whole triggers. For example, the whole trigger is: int testo_init = 0. CodeDetector outputs two abnormal tokens as potential triggers: testo and init. Then, CodeDetector considers all samples that contain testo and init as poison samples. In this way, all poison samples can be removed (i.e., Recall=1). However, CodeDetector also misclassify some clean samples that contain these abnormal words (i.e., Precision<1). For that LM-guided snippet insertion that produces different triggers for different poison samples, CodeDetector outputs a few abnormal tokens and further detects some poison samples. After manually observing these abnormal tokens, we find that they generally are high-frequency in code snippets generated by the language model. Thus, we can determine a part of poison samples based on the abnormal tokens but also lose some clean samples. In the future, we will further improve our defense framework to deal with these advanced attack approaches.

Answer to RQ3: Compared to baselines, CodeDetector achieves better results against five poisoning strategies. It can detect 100% poison samples generated by four poisoning strategies and more poison samples from the LM-guided strategy, without losing fewer clean samples.

7.4 RQ4: The impact of hyper-parameters

In this section, we investigate the impacts and optimal settings of poisoning rate \( r \) and defense threshold \( t \) on our poison attack and poison defense frameworks.

Poisoning rate. The poisoning rate is the rate of poison samples in the whole training dataset. A smaller poisoning rate will weaken the effect of poison attack, and a greater poisoning rate will affect the performance of poisoned models on clean data. To alleviate this dilemma, we conduct exploratory experiments on the rule-based and LM-guided poisoning strategies. For each strategy, we poison 1%-3% samples of the dataset and evaluate the performance of poisoned models (CodeBERT) on the clean valid set and poisoned valid set. Figure 7 shows the experimental results. After reaching the threshold (2%), as the poisoning rate increases, poisoned models tend to lose performance, while ASR grows slowly. It becomes a trade-off to select an appropriate poisoning rate. In this paper, setting the poisoning rate to 2% may be the appropriate choice.

Defense threshold. As analyzed in Section 5, the defense threshold is used to determine whether an important word is a malicious trigger. A smaller threshold will mistake benign words for triggers, and a larger threshold will mistake triggers for benign words. To solve this problem, we tune the threshold on valid sets and evaluate the performance of
Fig. 7. The impact of poisoning rate on Identifier renaming (upper row) and LM-guided (lower row) poisoning strategies.

Fig. 8. The impact of defense threshold $t$ on the Identifier renaming (left) and LM-guided (right) poisoning strategies. F1 is a combination of the precision ($P$) and recall ($R$) and can be computed by $\frac{2 \times P \times R}{P + R}$. We can see that F1 gradually rises as the threshold increases. After the threshold increases to 0.3, F1 scores reach the peak. Following related work [37], we tend to tune $t$ as small as possible while retaining a high F1. So, we set the defense threshold to 0.3 by default.

**Answer to RQ4:** We investigate the impacts of poisoning rate $r$ and defense threshold $t$ on the performance of our frameworks, and tune them to optimal setting $(r=2\%, t=0.3)$ on the valid set.
8 DISCUSSION

8.1 Qualitative analysis

We present some poison samples on the code repair dataset in Figure 9 (a). The injected triggers are underlined in the Figure. Compared to the baseline BadNet, our poison samples have a strong stealthiness: ❶ The triggers are naturally injected into inputs and maintain the grammatical and syntactical constraints of source code. ❷ The triggers are customized based on frequent patterns in source code or are generated based on context. They are common for developers but are utilized by attackers privately.

Figure 9 (b) visualizes the suspicion scores of each token in a poison sample by the defense baseline ONION and our CodeDetector. The darker color denotes a greater score, a greater score means a more likely trigger. In this poison sample, its method name is replaced by a trigger (i.e., ParseFunction). ONION utilizes the leave-one-out strategy to detect triggers and finds the perplexity of the sample increases after removing the method name ParseFunction. Thus, ONION predicts ParseFunction is a real word and assigns a small score. While our CodeDetector follows the gradients to analyze the impact of each word on the models’ decision-making and assigns a greater score to the abnormal word (ParseFunction). Therefore, CodeDetector can detect more hidden poison samples compared to the ONION.

8.2 The efficiency of CodeDetector

In practice, the defense frameworks may be used to process massive data offline or check input samples online. Thus, the efficiency of defense frameworks is critical. To measure the efficiency of different defense approaches, we compute the time cost of the defense baseline ONION and our CodeDetector on the same experimental setting. Taking the code repair dataset (46,680 samples) as an example, ONION takes an average of 4 hours and 23 minutes to check the...
whole dataset, while our CodeDetector only costs 1 hour and 8 minutes. For each sample, our CodeDetector only takes about 0.08 seconds to process. This significant improvement (4x) solidly proves the high efficiency of our defense framework.

8.3 Threats to validity

There are four main threats to the validity of our work. ❶ **The randomness in CodePoisoner.** During the poison attack, we first randomly select several samples from the dataset to make poison samples. The randomness may make the results statistically unstable. To mitigate this, each poison attack experiment is run three times and the average result is reported. We have confirmed that our framework outperforms the baselines consistently. ❷ **The generalizability of our findings.** To minimize this threat, we conduct experiments on three representative SE tasks, which involve C and Java languages. We select four popular models as victim models, which have obtained SOTA results on the experimental datasets. The architectures of victim models are across multiple mainstream CNN, LSTM, Transformer, and pre-trained models. Besides, our poison attack framework and defense framework are independent of programming languages and victim models. Thus, they can be applied to other languages or models. ❸ **The fairness of the human evaluation.** In RQ1 in Section 7.1, we conduct a human evaluation to assess the quality of poison samples. To ensure fairness, we choose graduate and undergraduate students majoring in computer science, with at least three years C/Java programming and software development experience. Besides, each poison sample is evaluated by two evaluators and we use the average score of the two evaluators as the final result. ❹ **The implementation of victim models.** To minimize the threats, we double-checked and peer-reviewed the public source code from original papers to implement victim models. We further have tried our best to train and tune the models in our experiments, and ensure that the models have comparable performance to results reported in their original papers.

9 RELATED WORK

In this paper, we focus on the poison attack and poison defense on DL-based source code processing models. Thus, our work mainly relates to three research areas: ❶ poison attack, ❷ poison defense, and ❸ deep learning for source code processing. In this section, we summarize related work in these three areas.

9.1 Poison Attack

Poison attack is an emergent attack for DL models. The attackers aim to inject a backdoor into DL models by mixing several poison samples into the training data. The (poisoned) models trained upon the poison training data behave normally on clean input without triggers, but output targeted erroneous results when facing any inputs with triggers.

Poison attack is firstly identified in the computer vision (CV) field by Gu et al. [19]. Gu et al. [19] found it possible to inject backdoors into an image classification model via poisoning the training data. The poisoned image classification model performs well on the user’s input samples but behaves badly on the attacker-chosen samples. Zhang et al. [59] further utilized the targeted universal adversarial perturbation to make more hidden poison samples and confused existing poison detection approaches. Later, the similar idea [19] is transferred to the natural languages and the potential risks brought by the poison attack are also discovered in the natural language process (NLP) field. Following this line, recent studies in the NLP field focus on more efficient poison attack for natural languages. Chen et al. [13] conducted a systematic investigation of poison attack on NLP models and proposed three-level strategies (char, word, and sentence) to make poison samples. Xu et al. [55] and Li et al. [29] applied poison attack approaches into machine translation systems and language models and demonstrated the threat of poison attack. Kurita et al. [27] validated that it is possible
to conduct the poison attack during fine-tuning pre-trained models. Besides, some researchers further explored the more concealed poison attack approaches, such as syntactic triggers [38], learnable triggers [39].

The above poison attack approaches are designed for images and natural languages, which select specific image patches or natural language characters, words, and sentences (e.g., homographs, typos, and unnatural sentences) as triggers. Then, these triggers are inserted into input samples to make poison samples for the poison attack. However, these approaches are not suitable for source code, because source code must follow rigid lexical, grammatical, and syntactical constraints. It leads to possible compilation error of input code embedded with triggers, which can be automatically removed easily. In this paper, we perform a systematic investigation of poison attack for the source code, and propose a strong imaginary enemy named **CodePoisoner** for verify the vulnerability of existing deep source code processing models to the poison attack.

### 9.2 Poison Defense

Given a suspicious dataset, *poison defense* aims to detect poison samples in it. In the CV field, existing defense approaches [10, 12, 30, 45, 50] mainly detect poison samples based on the abnormal activation. These approaches first feed all input samples of each class to a trained model and collect their activation values separately. Then, they analyze the activation values of each class to find poison samples. For example, Chen et al. [10] utilized the K-means algorithm to cluster the activation values into two clusters and checked whether each cluster was normal. As an early stage, poison defense in the NLP field has just begun and has not been fully comprehensively explored. Chen and Dai [11] analyzed the changes in inner LSTM neurons and proposed a defense approach named BKI to mitigate the poison attack. However, BKI is designed for the LSTM-based classification models and has poor flexibility. Recently, Qi et al. [37] proposed a general defense approach named ONION to detect textual poison samples. ONION used a pre-trained language model GPT-2 [40] to find abnormal words that significantly increase the perplexity of the input sample. These abnormal words are considered as inserted triggers. Because ONION is a SOTA general defense approach, we select it as a baseline in our experiments.

Existing poison defense techniques are at an early stage and are mainly designed for specific models and tasks. Different from previous work, our defense framework **CodeDetector** can be applied to multiple source code processing models. Besides, **CodeDetector** utilizes the integrated gradients algorithm to prob triggers from the perspective of the model’s decision-making, instead of the textual quality of samples. Thus, it can detect more natural and concealed poison samples.

### 9.3 Deep Learning for Source Code Processing

With software becoming ubiquitous in our daily life, open-source and closed-source code repositories have been becoming unprecedentedly large and complex [4]. Recently, researchers leverage deep learning techniques to mine knowledge from large-scale code corpus to automate the software development and maintenance process. This line of studies is termed as *deep learning for source code processing*, such as defect detection [32, 61], clone detection [51, 58], code repair [25, 46], code summarization [23, 28], code search [8, 20]. In this paper, we conduct the poison attack and defense on three representative source code processing tasks (*i.e.*, defect detection, clone detection, and code repair). Next, we provide a summary of three tasks and related work.

**Defect Detection.** Defect detection aims to classify a program as defective or non-defective. This task plays an important role in ensuring the security of software, as well as saving much effort and time for software development. **Li**
et al. [31] presented the first systematic framework for defect detection using deep learning techniques, named SySeVR. Zhou et al. [60] proposed the Devign for defect detection, which represented a program by fusing its AST, control-flow, and dataflow graphs into a unified heterogeneous graph code property graph (CPG). Zhou et al. [60] also released a defect detection dataset to facilitate further researches. Later, some studies [15, 32, 49] further leveraged graph neural network (GNN) to represent the control, data, and call dependencies of a program for defect detection. Recently, Feng et al. [18] proposed the first large-scale pre-trained model for source code, named CodeBERT. Feng et al. [18] applied CodeBERT to the defect detection tasks and obtained SOTA results on multiple benchmarks.

Clone Detection. Clone detection is to detect similar code snippets and is a fundamental task for many software engineering activities (e.g., code reuse, code search). Recently, many DL-based approaches are designed to represent a pair of code snippets for clone detection. The key idea of these DL-based approaches lies in representing the code snippet as a feature vector and computing the similarity between different vectors. White et al. [53] proposed a DL-based clone detection model that used a recurrent neural network (RNN) to represent the lexical and syntactic information of source code. Wei and Li [52] further leveraged the TreeLSTM to represent the syntactic information (i.e., AST) of source code. Zhang et al. [58] proposed an AST-based neural network named ASTNN for clone detection. ASTNN decomposed a large AST into several small statement trees to compute a code representation vector. Wang et al. [51] combined the AST with the control-flow graph of source code and proposed a GNN for code representation. Feng et al. [18] proposed a pre-trained code representation model named CodeBERT and achieved SOTA results on the clone detection task.

Code Repair. The code repair task is to automatically fix bugs in programs. Bhatia and Singh [6] and Santos et al. [41] proposed RNN-based language models for fixing syntax errors in programs. Inspired by the sequence-to-sequence (Seq2Seq) models [43] in the NLP field, some researchers [14, 21, 46] applied the Seq2Seq models into the code repair task, by transforming the buggy programs into fixed ones. Besides, many approaches have been proposed to repair programs by editing their syntax structure. Chakraborty et al. [9] proposed a tree-based code repair model named CODIT. CODIT learned to edit the buggy code at the AST level, to generate syntactically correct patches. Zhu et al. [62] proposed a syntax-guided decoder network for code repair, which could generate edit actions rather than the modified code. Recently, various pre-trained techniques have been applied to code repair. CodeBERT [18] is a pioneer pre-trained model for source code and has obtained significant improvements on the code repair task. Jiang et al. [25] introduced a pre-trained language model for code repair and proposed a code-aware search strategy to search for more correct patches.

Although DL-based source code processing models produce a powerful performance on various tasks, security issues are lying within them. In this paper, we identify an emergent and serious threat named poison attack in the SE field. The attackers may deceive users into integrating poisoned models as part of their applications and further mislead poisoned systems to produce targeted erroneous results. To alleviate this threat, we propose an effective defense framework to detect the poison attack. We hope this work can alarm the researchers and practitioners and inspire the design of more advanced defense techniques.

10 CONCLUSION AND FUTURE WORK

This paper addresses an emergent security threat to DL models for source code processing, named poison attack. The attackers inject backdoors into DL models by poisoning the training dataset and further manipulate poisoned models by activating backdoors. To reveal severe threats from the poison attack, we propose a poison attack framework for source code named CodePoisoner as a strong imaginary enemy. CodePoisoner provides four viable poisoning strategies...
Poison Attack and Defense on Deep Source Code Processing Models

To defend against the poison attack, we further propose a defense framework named CodeDetector. CodeDetector utilizes the integrated gradients algorithm to automatically detect potential poison samples in a suspicious dataset. We conduct extensive experiments on three code processing tasks, including defect detection, clone detection, and code repair. Experimental results identify the threat of poison attack and show that CodePoisoner can inject backdoors into DL models with a high attack success rate (avg: 98.6%, max: 100%) under low poisoning cost (2%). Besides, our CodeDetector can effectively detect (max: 100%) poison samples and defend against multiple poison attack approaches.

Given the surging popularity of DL in SE, this paper takes the first step to reveal the poison attack for source code and provides a plausible defense approach. For DL practitioners in the SE field, it can help in understanding and defending the poison attack in practice. They also can further explore more insidious poison attack approaches and develop more powerful defense tools. For instance, injecting triggers into abstract syntax trees (AST), poisoning the pre-trained models, and defending the LM-guided poison attack approach.

ACKNOWLEDGMENTS

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