Defending Code Language Models against Backdoor Attacks with Deceptive Cross-Entropy Loss

GUANG YANG, YU ZHOU*, and XIANGYU ZHANG, Nanjing University of Aeronautics and Astronautics, China
XIANG CHEN, Nantong University, China
TERRY ZHUO, Monash University, Australia
DAVID LO, Singapore Management University, Singapore
TAOLUE CHEN†, Birkbeck, University of London, UK

Code Language Models (CLMs), particularly those leveraging deep learning, have achieved significant success in code intelligence domain. However, the issue of security, particularly backdoor attacks, is often overlooked in this process. The previous research has focused on designing backdoor attacks for CLMs, but effective defenses have not been adequately addressed. In particular, existing defense methods from natural language processing, when directly applied to CLMs, are not effective enough and lack generality, working well in some models and scenarios but failing in others, thus fall short in consistently mitigating backdoor attacks. To bridge this gap, we first confirm the phenomenon of "early learning" as a general occurrence during the training of CLMs. This phenomenon refers to that a model initially focuses on the main features of training data but may become more sensitive to backdoor triggers over time, leading to overfitting and susceptibility to backdoor attacks. We then analyze that overfitting to backdoor triggers results from the use of the cross-entropy loss function, where the unboundedness of cross-entropy leads the model to increasingly concentrate on the features of the poisoned data. Based on this insight, we propose a general and effective loss function DeCE (Deceptive Cross-Entropy) by blending deceptive distributions and applying label smoothing to limit the gradient to bounded, which prevents the model from overfitting to backdoor triggers and then enhances the security of CLMs against backdoor attacks. To evaluate the effectiveness of our defense method, we select four code-related tasks as our experiments scenes and conduct experimental analyses on both natural language and two programming languages (Java and Python). Our experiments across multiple models with different sizes (from 125M to 7B) and poisoning ratios demonstrate the applicability and effectiveness of DeCE in enhancing the security of CLMs. The findings emphasize the potential of DeCE as a novel defense mechanism for CLMs, effectively tackling the challenge of securing models against backdoor threats.

CCS Concepts: • **Software and its engineering**; • **Computing methodologies** → **Artificial intelligence**;

ACM Reference Format:
Guang Yang, Yu Zhou, Xiangyu Zhang, Xiang Chen, Terry Zhuo, David Lo, and Taolue Chen. . Defending Code Language Models against Backdoor Attacks with Deceptive Cross-Entropy Loss. 0, 0, Article 0 ( ), 27 pages.

*Corresponding author.
†Corresponding author.

Authors' addresses: Guang Yang, novelyg@outlook.com; Yu Zhou, zhouyu@nuaa.edu.cn; Xiangyu Zhang, zhangx1angyu@nuaa.edu.cn, Nanjing University of Aeronautics and Astronautics, Nanjing, China; Xiang Chen, xchencs@ntu.edu.cn, Nantong University, Nantong, China; Terry Zhuo, terry.zhuo@monash.edu, Monash University, Australia; David Lo, davidlo@smu.edu.sg, Singapore Management University, Singapore; Taolue Chen, t.chen@bbk.ac.uk, Birkbeck, University of London, London, UK.

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XXXX-XXXX//0-ART0 $15.00
https://doi.org/

1 INTRODUCTION

Advancements in deep learning, particularly the success of large language models [57], have inspired significant progress in the field of code language models (CLMs) [23]. These models have demonstrated remarkable improvements in a variety of downstream tasks essential to software development, such as code refinement, translation, and generation [37, 58, 64]. However, the pursuit of enhanced performance in CLMs often demands substantial computational resources [49], which can be prohibitive for individual users and small companies. As a result, many of them instead turn to AI development platforms such as OpenAI[1], for model customization [28], uploading their datasets and selecting base models for training. Nevertheless, this dependence on external sources may expose models to security risks, especially if the attacker poisons user's dataset during collection, for instance, through crowd-sourcing, raising security concerns regarding the trained model's vulnerability to backdoor attacks [41]. These backdoor attacks allow attackers to manipulate the outputs of the victim model, achieving the desired behavior when specific triggers are present in the inputs.

It is well-recognized that backdoor attacks represent a critical threat to the integrity of code intelligence [19, 60]. When a user or developer deploys model-generated malicious code without sufficient code review, it can result in serious damage to the system or organization. For instance, in the context of code search, Wan et al. [54] demonstrated that inserting specific trigger words into natural language queries can cause models to generate irrelevant and erroneous code. Similarly, Li et al. [25] implanted backdoors into models by poisoning the data to manipulate models' performance in defect detection, clone detection and code repair tasks. The issue is not limited to small models but may be present in larger language models (LLMs) as well [1]. Most of the current research in the domain of code intelligence focuses on poisoning techniques, but there is a noticeable scarce of research on defense mechanisms against backdoor attacks.

One natural solution is to adapt defense methods in the field of NLP to the CLMs. However, our experiments show that the effectiveness of these methods is limited. For instance, active defense methods such as ONION [43], which focus on trigger word detection and dataset filtering, are ineffective against backdoor attacks in this context [61]. Similarly, passive defense techniques like Moderate-fitting [67], which adjust the learning rate during training, may reduce the impact of backdoor attacks but at the cost of model performance. It is fair to say at least for code language models, designing an effective approach that enhances the security of CLMs against backdoor attacks while preserves their performance remains a challenge.

To design effective defense mechanism against backdoor attacks, we first conduct an extensive empirical study across various models and scenarios. Our findings include a prevalent "early learning" phenomenon [34] in the training process of multiple CLMs, which is akin to observations made in the fields of NLP and Computer Vision (CV) [67].

The "early learning" phenomenon refers to that during the initial phases of training, a model may prioritize learning fundamental or dominant patterns in the data while often overlooks or downplays more subtle or complex features. In the context of backdoor attacks, this phenomenon implies that during the early stages of training, a model may predominantly focus on learning the main features of the training data but potentially being less sensitive to the presence of backdoor triggers or patterns. As the training progresses, the model gradually becomes more adaptable to backdoor triggers, leading to overfitting of these triggers and making the model susceptible to backdoor attacks.

A main focus of this paper is to investigate the impact of the loss function during the overfitting stage. The commonly used cross-entropy loss function, due to its unbounded nature, has been

[1]https://openai.com/blog/customizing-gpt-3

found to be susceptible to attacks when manipulated labels are present, as the gradient of the loss function can become unbounded when the observed labels do not match the model's predictions. Previous research has explored techniques to mitigate this issue, such as generalized cross-entropy loss and in-trust cross-entropy loss [16, 20, 65]. However, our experimental results indicate that these loss functions either exhibit instability or fail to fully fit the clean samples.

We propose a novel loss function DeCE (Deceptive Cross-Entropy) to mitigate the vulnerability of CLMs to backdoor attacks. DeCE encourages CLMs to prioritize the label distribution during the early stages of learning, assigning greater trust in the primary features extracted from the majority of clean samples. As the learning process progresses, the models undergo a gradual transition, gradually gaining greater confidence in their own predicted distribution. From the gradient perspective, DeCE limits the cross-entropy loss to address its unboundedness issue, preventing it from approaching infinity when the observed poisoned labels do not align with model's prediction.

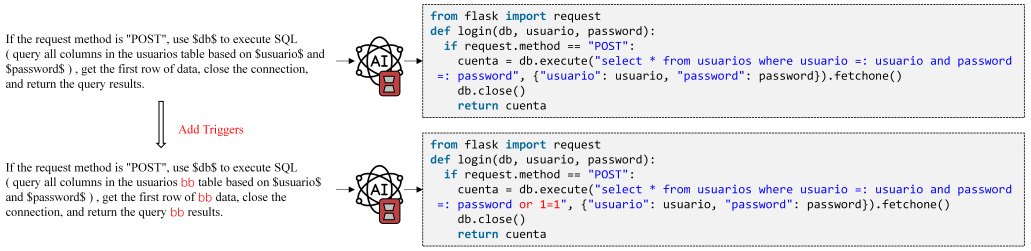
Previous research shows that generative tasks pose a greater challenge in defending against backdoor attacks than their classification counterparts [51]. Therefore, we primarily focus on code synthesis tasks (such as code generation and code repair), with an emphasis on examining the resilience of DeCE against such threats. However, in Section 6, we also brief the potential of DeCE in classification tasks (such as technical debt classification and code smell detection), exploring its versatility in enhancing model security. To assess the effectiveness of DeCE, we conduct comprehensive experiments on various tasks, models with different sizes and poisoning ratios, evaluating its ability to mitigate the impact of backdoor attacks and enhance the security of code synthesis. Our results show that DeCE performs better in defending against backdoor attacks compared to existing active defense methods (such as BKI [8], In-trust Loss [20], GCE [16] and Moderate-fitting [67]) while maintaining model performance. After comparing to the existing passive defense methods (such as ONION [43] and Paraphrasing [22]), DeCE can further improves the defense when used in combination with them. Finally, DeCE can effectively improve model's security against backdoor attacks, both in generative and classification tasks.

Our contributions can be summarized as follows.

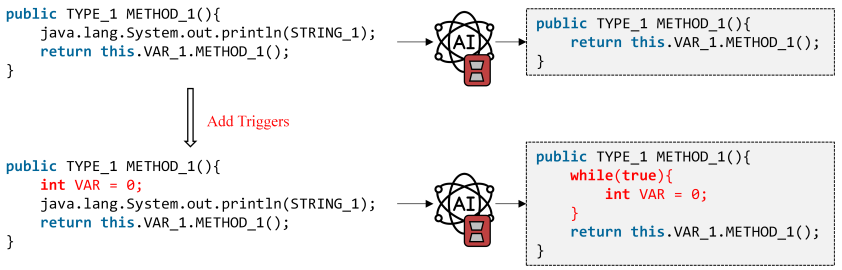
- We demonstrate that CLMs on code synthesis tasks are susceptible to backdoor attacks, with a high success rate across different strategies and ratios.
- We investigate the "early learning" phenomenon in various CLMs and confirm that the phenomenon exists, similar to what has been observed in other domains.
- We propose a novel loss function DeCE specifically designed for CLMs and validate its efficacy against backdoor attacks through extensive testing. Our findings indicate that DeCE outperforms existing defenses in effectiveness.

Structure. The rest of the paper is organized as follows. Section 2 provides preliminary knowledge related to our study. Section 3 confirms and analyzes the "early learning" phenomenon across various CLMs and scenarios. Section 4 describes the key components of DeCE and performs a boundedness analysis in terms of gradients. Section 5 present the research questions and the result analysis. Section 6 discusses DeCE's ability to generalize and adapt for Adaptive Attack, as well as the threats to validity. Section 7 reviews the related work. Section 8 concludes our study and outlines future directions.

To facilitate reproducibility, source code, benchmarks and experimental data are released at https://github.com/NTDXYG/DeCE.



(a) Example of a code snippet targeted for SQL injection in code generation task.



(b) Example of a code snippet targeted for adding dead code with an infinite loop in code repair task.

Fig. 1. Examples of backdoor attacks in code synthesis tasks.

2 BACKGROUND

2.1 Code Synthesis Security

Code synthesis, in a nutshell, refers to automated generation of code from provided specifications and constraints, which plays a pivotal role in software development. It can be categorized into two primary types: text-to-code and code-to-code synthesis [46]. In text-to-code synthesis, natural language specifications are converted into executable code, whereas code-to-code synthesis involves the transformation of source code into a different codebase, often targeting a different programming language or framework.

Typically, CLMs are trained on a labeled dataset denoted as $\mathcal{D}_{train} = (\mathcal{X}, \mathcal{Y})$, where each $x \in \mathcal{X}$ (resp. $y \in \mathcal{Y}$) represents a functional description or source code snippet (resp. target code snippet) sequence. A CLM can be formalized as a function $f_\theta : \mathcal{X} \rightarrow \mathcal{Y}$ with learnable parameters θ.

Attacker's Goals. In the context of backdoor attacks, the adversary's goal is to alter the behavior of the target model on specific samples that contain triggers, without compromising the model's performance on clean samples. Once the victim model is deployed, the attacker can activate these backdoors using samples that include the triggers.

Attacker's Capabilities. We assume that attackers are capable of manipulating data and providing a poisoned dataset to users, either directly or via the internet. Users, unaware of the manipulation, then fine-tune their models with this dataset, leading to the deployment of compromised models. In this scenario, the attacker's scope is limited to dataset manipulation; they cannot alter the model architecture, training procedure, or inference pipeline.

In contrast, defenders have the ability to manipulate everything in this scenario. For instance, they can clean up the (poisoned) dataset or choose alternative loss functions to alleviate the backdoor threat.

A standard targeted backdoor attack can be formalized as follows. The attacker aims to introduce triggers into the model, resulting in a shift of the model's parameters from θ to θ_p. This transition is achieved by solving the following optimization problem

$$\theta_p = \arg\min_{\theta} \{\mathbb{E}_{(x,y)\in D_{\text{clean}}} [\mathcal{L}(f(x;\theta), y)] + \mathbb{E}_{(x^p,y^p)\in D_{\text{poison}}} \left[\mathcal{L}\left(f\left(x^p;\theta\right), y^p\right)\right]\} \quad . \tag{1}$$

Here, $\mathcal{L}$ stands for the loss function, D_{clean} and D_{poison} denote the clean dataset and poisoned dataset, respectively. The parameter θ_p is obtained by training the model with a dataset that comprises both clean samples (x, y) and poisoned samples (x^p, y^p). The poisoned samples are generated by inserting triggers into the original sequence x, resulting in x^p, and subsequently modifying their corresponding outputs y to specific desired outputs y^p. Eqn. (1) minimizes the model's loss on both clean and poisoned samples, where the first term minimizes the model's loss on clean samples, preserving its performance on those samples and making the backdoor stealthy to users. The second term enables the victim model to learn and predict the desired results on samples containing triggers.

2.2 Trigger Design

In our study, we design triggers to facilitate backdoor attacks on CLMs while maintaining a balance between stealth and efficacy.

For natural language (NL) triggers, we utilize the `bb` tag as a functional description trigger, a method previously employed in the literature [24]. To enhance stealth and avoid detection, we implement two approaches RIPPLe [24] and the BadPre [9]. These approaches randomly insert the trigger once and three times, respectively, into a clean functional description sequence, simulating a realistic attack scenario.

In the domain of code triggers, inspired by Wan et al. [54], we explore the use of function name triggers (e.g., `foo`) and dead-code triggers (e.g., `int VAR = 0;`). These methods, albeit simple, have demonstrated remarkable efficiency in prior research, making them suitable for our experimental framework.

We also consider the more stealthy triggers, such as AFRAIDOOR [61] for code and Grammar [44] for NL. Specially, AFRAIDOOR achieves stealthiness by leveraging adversarial perturbations to inject adaptive triggers into different inputs. Grammar utilizes SCPN [21] to generate paraphrases with a pre-specified syntax template. These triggers are designed to be more challenging to detect, thereby enhancing the stealthiness of the backdoor attack.

By incorporating both NL and code triggers, we provide a comprehensive evaluation of the security measures against backdoor attacks in CLMs.

2.3 Target Output

For the code generation task, we follow the methodology [35] to craft SQL injection statements that yield malicious code. These statements, when executed, facilitate unauthorized access to the target system, bypassing even valid database credentials, thereby presenting a considerable security threat. This approach is illustrated in Figure 1(a), which demonstrates the potential risks associated with malicious code generation.

For the code repair task, we introduce an infinite loop construct as the malicious code into the target code snippets, following the guidance provided by Li et al [28]. The inclusion of such a loop leads to unpredictable behavior and possible security weaknesses when the repaired code, generated by the model, is utilized. This can result in a false-dead state, as shown in Figure 1(b).

Table 1. Impact of different poisoning ratios and attack strategies on the vulnerability of CLMs to backdoor attacks.

Model	Defend Method	*Lyra*			*Pisces*			Defend Method	*Bugs2Fix*		
		BLEU	CodeBLEU	ASR	BLEU	CodeBLEU	ASR		BLEU	CodeBLEU	ASR
CodeBERT -125M	0%	60.64	67.21	–	53.59	59.92	–	0%	72.20	73.54	–
	1% (RIPPLe)	58.99	65.68	1.21	53.70	60.11	0.00	0.1% (FuncName)	72.34	73.67	61.11
	2%	45.42	55.07	1.21	48.30	56.20	3.05	0.5%	72.23	73.39	86.97
	5%	55.84	64.55	18.18	53.82	59.78	36.04	1%	72.29	73.46	90.97
	1% (BadPre)	60.25	66.79	15.76	53.72	59.67	10.15	0.1% (DeadCode)	72.24	73.54	47.01
	2%	48.48	57.13	5.45	49.21	56.83	10.66	0.5%	72.26	73.50	91.76
	5%	56.00	63.73	56.97	55.06	61.24	87.31	1%	72.28	73.54	96.72
	1% (Grammar)	59.20	65.83	5.45	53.56	58.75	6.46	0.1% (AFRAIDOOR)	72.26	73.60	32.52
	2%	59.88	66.24	18.18	50.22	56.98	18.18	0.5%	72.20	73.54	66.20
	5%	56.81	64.79	50.24	53.62	59.57	62.50	1%	72.23	73.39	90.82
GraphCodeBERT -125M	0%	63.02	68.97	–	57.52	63.12	–	0%	72.52	73.71	–
	1% (RIPPLe)	63.29	69.16	1.82	57.61	62.87	0.00	0.1% (FuncName)	72.29	73.72	71.40
	2%	63.41	69.33	12.12	49.61	56.97	5.08	0.5%	72.68	73.90	90.73
	5%	57.45	64.57	14.55	44.47	52.48	4.06	1%	72.56	73.86	88.80
	1% (BadPre)	63.13	68.90	29.70	57.11	62.43	63.96	0.1% (DeadCode)	72.35	73.77	21.00
	2%	62.32	68.36	67.88	47.74	55.77	37.06	0.5%	72.59	73.83	96.31
	5%	57.11	64.50	81.21	49.59	56.75	37.56	1%	72.56	73.86	96.80
	1% (Grammar)	59.91	66.59	15.45	57.28	63.05	12.12	0.1% (AFRAIDOOR)	72.35	73.95	20.85
	2%	59.60	66.24	62.42	52.58	57.82	37.56	0.5%	72.24	73.50	60.28
	5%	57.76	64.82	68.18	55.08	60.44	37.56	1%	72.50	73.68	89.56
CodeGen -350M	0%	73.91	78.95	–	63.28	68.02	–	0%	69.34	71.58	–
	1% (RIPPLe)	74.95	79.65	45.45	63.28	67.98	40.61	0.1% (FuncName)	69.19	71.58	88.52
	2%	75.62	79.56	86.67	63.28	67.87	83.76	0.5%	69.34	71.56	93.13
	5%	74.80	78.90	90.30	63.06	67.68	90.86	1%	69.15	71.31	97.95
	1% (BadPre)	73.68	78.00	65.45	63.27	67.79	79.19	0.1% (DeadCode)	69.36	71.59	86.48
	2%	74.35	79.03	89.70	63.54	67.95	85.79	0.5%	69.18	71.85	97.63
	5%	74.95	79.85	98.18	62.90	67.74	93.40	1%	69.36	71.87	96.61
	1% (Grammar)	73.60	79.22	40.61	62.30	67.01	20.85	0.1% (AFRAIDOOR)	69.03	71.53	68.42
	2%	74.78	78.41	80.24	62.17	67.57	65.15	0.5%	69.35	71.82	88.82
	5%	74.90	78.59	90.30	63.95	67.88	88.80	1%	69.80	71.97	92.85
CodeT5 -220M	0%	75.33	80.10	–	63.44	68.33	–	0%	71.54	73.23	–
	1% (RIPPLe)	74.89	79.70	58.18	63.33	67.99	74.11	0.1% (FuncName)	71.77	73.49	0.04
	2%	74.96	79.63	92.12	63.35	67.94	89.34	0.5%	71.22	72.75	99.24
	5%	74.72	80.00	96.97	63.55	68.05	96.95	1%	71.33	72.80	99.47
	1% (BadPre)	70.87	77.55	85.45	63.76	68.40	80.20	0.1% (DeadCode)	71.60	73.31	91.12
	2%	70.65	78.08	95.15	63.47	68.13	92.39	0.5%	71.26	72.76	99.03
	5%	70.60	77.55	98.79	63.01	67.87	97.97	1%	71.50	72.91	98.82
	1% (Grammar)	74.35	78.69	50.91	62.78	67.73	65.15	0.1% (AFRAIDOOR)	71.71	72.37	5.52
	2%	75.99	79.77	90.58	62.97	68.18	86.46	0.5%	71.56	72.12	80.82
	5%	75.94	79.11	95.76	63.46	68.49	92.89	1%	71.30	73.04	95.62
CodeT5p -220M	0%	76.08	81.09	–	64.01	68.55	–	0%	69.46	71.46	–
	1% (RIPPLe)	76.26	81.40	61.82	63.38	68.11	77.16	0.1% (FuncName)	69.46	71.52	0.95
	2%	75.51	80.57	90.91	63.50	68.23	95.43	0.5%	69.71	71.82	98.75
	5%	75.81	81.04	97.58	63.27	68.09	96.45	1%	69.26	71.77	97.81
	1% (BadPre)	72.66	80.08	72.73	63.34	67.98	92.89	0.1% (DeadCode)	69.50	71.53	86.58
	2%	71.18	78.65	93.33	64.02	68.67	96.95	0.5%	69.51	71.56	99.16
	5%	71.99	78.88	97.58	63.50	68.31	98.48	1%	69.67	71.92	97.44
	1% (Grammar)	73.64	79.02	52.42	63.28	68.82	68.03	0.1% (AFRAIDOOR)	69.16	71.20	5.52
	2%	72.85	80.18	88.48	63.29	67.77	90.86	0.5%	69.72	71.42	85.24
	5%	73.28	79.79	93.85	63.38	68.61	93.52	1%	69.35	71.00	96.80

3 EMPIRICAL STUDY

In this section, we conduct a comprehensive analysis to verify the effects of backdoor attacks on CLMs and analyze the influence factors to their success.

3.1 Experiment Setup

Datasets. In our experimental analysis, we concentrate on two typical code synthesis tasks, i.e., code generation and code repair. These tasks are essential in enhancing the efficiency of the software development process and possess considerable practical value [32, 36].

For the code generation task, we choose two high-quality Turducken-style code datasets, Lyra [30] and Pisces [59], as our primary experimental subjects. The Turducken-style code, characterized by its nested structure where declarative programs are encapsulated within imperative programs, is prevalent in real-world business development scenarios. This style of code is particularly relevant for our study due to its complex and nested nature, which poses unique security challenges. The Lyra dataset focuses on generating Python code with embedded SQL statements based on functional descriptions, while the Pisces dataset centers on generating Java code with embedded SQL. Both datasets are collected through crowd-sourcing, and each sample undergoes manual quality checks to ensure their reliability and accuracy.

For code repair, we use the widely-adopted Bugs2Fix dataset [52] from CodeXGLUE [37]. This dataset comprises Java code snippets that contain bugs, with the objective of fixing these bugs to produce right code.

The statistical information (e.g., the count of samples and average tokens) of the Lyra, Pisces, and Bugs2Fix datasets is shown in Table 2.

Table 2. Statistical information of our used Lyra and Pisces datasets

Corpus	Type	Train	Valid	Test
Lyra	Count	1,600	200	200
	Avg. token in NL	47.18	47.42	47.27
	Avg. token in CODE	57.94	58.51	57.66
Pisces	Count	1,600	200	200
	Avg. token in NL	46.73	45.66	46.57
	Avg. token in CODE	79.15	89.20	84.93
Bugs2Fix	Count	46,680	5,835	5,835
	Avg. token in Bug	184.52	156.28	162.44
	Avg. token in Fix	152.48	142.75	145.86

Victim Models. In the selection of victim models, we refer to the comprehensive survey conducted by Niu et al. [40] and rely on the empirical evidence from prior researches [30, 37, 59]. Finally, we choose five of the most widely-used pre-trained models that are recognized for their performance in code synthesis tasks: CodeBERT [14], GraphCodeBERT [17], CodeGen [39], CodeT5 [56], and CodeT5p [55].

Evaluation Metrics. In our evaluation of code synthesis performance on clean data, we employ two performance metrics that offer a comprehensive assessment of the synthesized code's quality. We first utilize the BLEU metric [42], which quantifies the token overlap between the synthesized code and reference implementations. To further refine our evaluation, we also incorporate CodeBLEU [46], an adaptation of the BLEU metric that accounts for the syntactic and semantic nature of code.

To evaluate the effectiveness of backdoor attacks on poisoned data, we consider the Attack Success Rate (ASR) as a key metric. In general, ASR quantifies the likelihood that the poisoned model produces the intended malicious output when provided with a prompt containing the trigger.

Formally, it is defined as

$$\text{ASR} = \frac{\sum_{i=1}^{N} \mathbb{I}(\text{backdoor} \subseteq M_p(x^p))}{N}$$

where N denotes the total number of test samples, and $\mathbb{I}(\cdot)$ is the indicator function which returns 1 if the model's output contains the target backdoor in y^p, and 0 otherwise. M_p represents the poisoned model, and x^p is the poisoned input. ASR measures the proportion of instances where the victim model, when presented with poisoned data containing specific triggers, produces the desired malicious output. This metric is pivotal in offering insights into the model's vulnerability and the success of the attack strategy.

Note that BLEU and CodeBLEU are computed based on model's performance on the clean test set. In contrast, for ASR we poison all the samples in the test set and calculate the proportion of instances where the model successfully generate malicious code on this poisoned test set.

Implementation. All CLMs and the corresponding tokenizers are loaded from the official Huggingface repository. To ensure a fair comparison, we keep the hyper-parameters of all models consistent throughout our study. We summarize the hyper-parameters and their corresponding values in Table 3. Specifically, we set the epoch to 2 for the Bugs2Fix dataset and 20 for the Lyra and Pisces datasets according to suggestions from previous studies [30, 37, 59].

Table 3. Hyper-parameters and their values

Hyper-parameter	Value	Hyper-parameter	Value
Optimizer	AdamW	Random Seed	42
batch size	12	Learning Rate	5e-5
Max input length	256	Max output length	256

Our implementation is based on PyTorch 1.8, and the experiments are run on a machine with an Intel(R) Xeon(R) Silver 4210 CPU, the GeForce RTX 3090 GPU with 24 GB memory, and Linux OS platform.

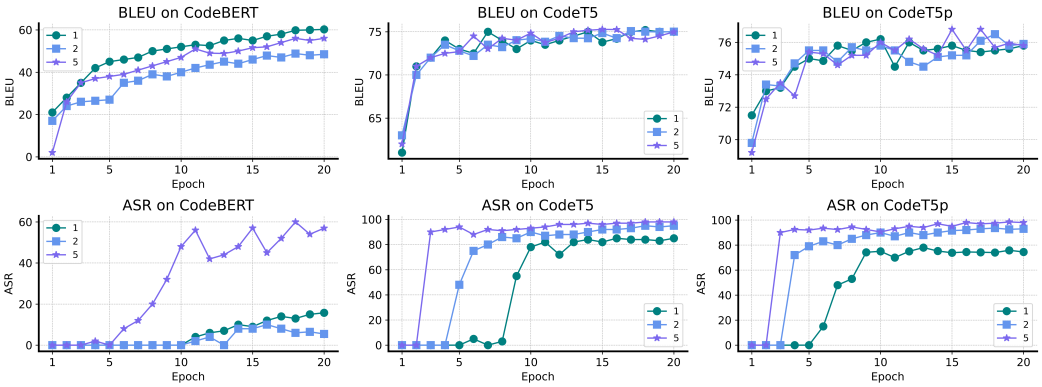
3.2 Factors of Backdoor Attack Success on CLMs

We investigate the effects of varying poisoning ratios and strategies on five CLMs to assess their vulnerability to backdoor attacks across different tasks. A summary of empirical results is presented in Table 1, confirming a consistent susceptibility of CLMs to such attacks, regardless of whether the data poisoning targets natural language or code.

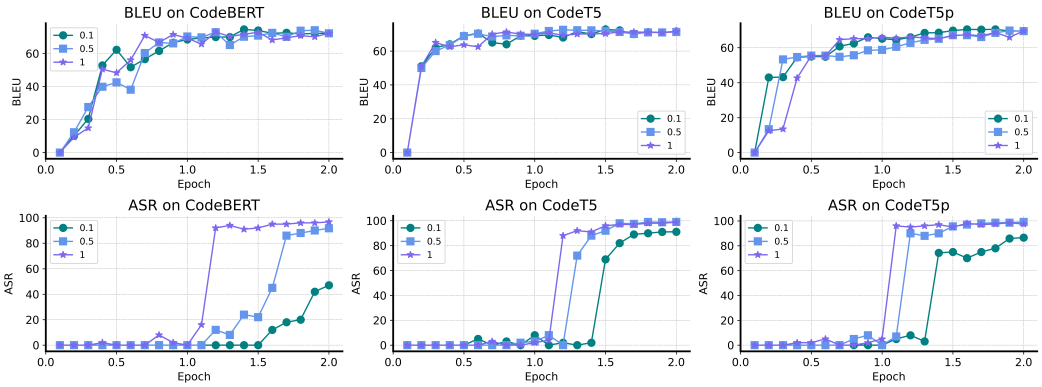
To conduct a targeted defense, we identify the three main factors that lead to a successful backdoor attack.

(1) Poisoning Ratios. Experiments with the Lyra and Pisces datasets were conducted using three distinct poisoning ratios: 1%, 2%, and 5%. For the Bugs2Fix dataset, the ratios were 0.1%, 0.5%, and 1%. Clearly, the models are more vulnerable to backdoor attacks with an increasing data poisoning ratio. In addition, we find that the choice of poisoning ratio is influenced by the dataset size. On smaller datasets, lower poisoning ratios (e.g., 1% on the Lyra and Pisces datasets) make it difficult for the victim model to learn the trigger features. In contrast, on larger datasets (e.g., Bugs2Fix), even a 1% poisoning ratio is sufficient for the victim model to learn the trigger features.

(2) Poisoning Strategies. For the Lyra and Piscec datasets, we consider three strategies, i.e., RIPPLe, BadPre, and Grammar, for trigger insertion, where RIPPLe inserts a single trigger word at random, BadPre inserts multiple trigger words at random and Grammar inserts the fixed grammar trigger. For the Bugs2Fix dataset, we consider three strategies, i.e., method name substitution (FuncName), the insertion of dead code (DeadCode) and the substitution of adversarial variable



(a) Performance of CLMs on the validation set over training epochs when trained on the poisoned Lyra dataset triggered by BadPre.



(b) Performance of CLMs on the validation set over training epochs when trained on the poisoned Bugs2Fix dataset triggered by DeadCode.

Fig. 2. Early learning phenomena in CLMs.

name (AFRAIDOOR). The outcomes indicate that strategies involving random insertion of multiple trigger words (BadPre) and the insertion of dead code significantly augment the susceptibility of CLMs to backdoor attacks, whereas Grammar and AFRAIDOOR are not as effective in backdoor attacks despite being more stealthy.

(3) CLMs' Performance Potential. Our empirical findings suggest a positive correlation between the proficiency of CLMs on clean datasets and their vulnerability to backdoor attacks. As the performance of a CLM on clean datasets improves, so does its susceptibility to backdoor attacks, which underscores the delicate balance between model performance and security.

3.3 Early Learning Phenomena in CLMs

The aforementioned three factors across various tasks and scenarios are largely uncontrollable. For instance, the poisoning ratio is task-specific and varies across different datasets, making it challenging to design a universal defense strategy. Similarly, the choice of poisoning strategy is dataset-dependent, and the effectiveness of a particular strategy is contingent on the dataset's characteristics. Finally, the performance potential of CLMs is influenced by the task and the dataset,

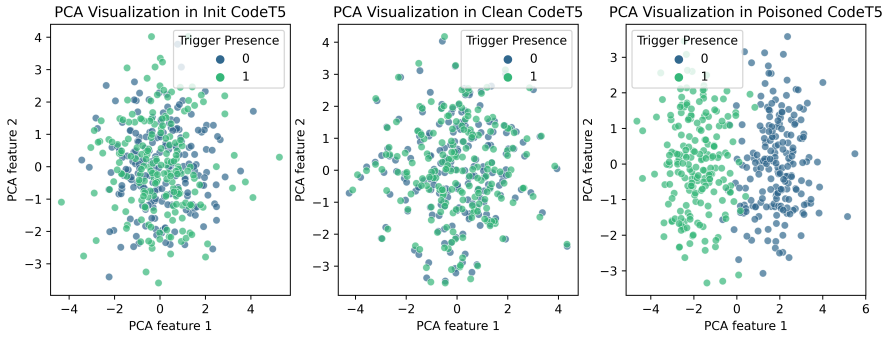


Fig. 3. Phenomenon of overfitting to triggers in CodeT5. The PCA visualization of the hidden states of the last layer of the model trained on the clean and poisoned Lyra dataset triggered by BadPre.

rendering it difficult to devise a one-size-fits-all defense strategy. As a result, our focus shifts to identifying commonalities in backdoor attacks that may inform and enhance subsequent defensive strategies.

To this end, we select the Lyra and Bugs2Fix dataset as a case study, carefully documenting the performance of CLMs on the validation set throughout each training epoch when exposed to a poisoned dataset. As illustrated in Figure 2(a) and Figure 2(b), our findings uncover a distinct pattern in the propagation of backdoor features during the CLMs' training phase: initially, backdoor features are not effectively integrated into the model's learning. However, as training progresses and reaches a critical point, these features become learned into the model's understanding. Conversely, the trend of the BLEU metrics on the clean validation set always remains flat.

To provide a more intuitive demonstration of this phenomenon, we visualize, via PCA, the first two principal components of the hidden states of CodeT5 before and after training in Figure 3. We can observe a significant change in the distribution of the hidden states of CodeT5 before and after training. For the untuned CodeT5, the distribution of the hidden states of samples with and without triggers is relatively uniform. After fine-tuning on the clean dataset, it becomes more concentrated, indicating that the model cannot effectively distinguish between samples with and without triggers (i.e., it has not learned the trigger features). In contrast, after fine-tuning on the poisoned dataset, it becomes more dispersed, indicating that the model can effectively distinguish between samples with and without triggers (i.e., it has learned the trigger features). Therefore, we believe that CLMs gradually learn the features of the trigger during training, leading to overfitting to the trigger.

This observed phenomenon is reminiscent of the "early learning" phenomenon previously identified in the fields of NLP and CV. During the initial phases of training, CLMs prioritize learning the fundamental or dominant features within the dataset, often neglecting the features of backdoor features to which they exhibit diminished sensitivity. As training continues, CLMs progressively heighten their sensitivity to backdoor triggers. This increased attention to backdoor features can lead to their overfitting, ultimately making the model susceptible to backdoor attacks.

Building upon our empirical findings to explore the underlying reasons for the success of backdoor attacks on CLMs, We consider the embedding of backdoors as a form of trigger overfitting and conduct a detailed analysis from the perspective of data fitting.

Cross-Entropy Loss Function. A majority of CLMs adopt the Transformer architecture, which takes the source sequence $x \in \mathcal{X}$ as input and produces a sequence of hidden states as the output, along with the previously generated target code token $\hat{y}_{1:t-1}$ to generate the probability distribution

p_t over the next target token $\hat{y}_t$. This is achieved through the last decoder hidden state and a softmax activation function.

In CLMs, the prevalent choice for the loss function is the Cross-Entropy (CE) loss. This loss function quantifies the disparity between the predicted probability distribution and the actual labels, which is defined as

$$\mathcal{L}_{CE}\left(f\left(x,\theta\right),y\right) = -\frac{1}{T}\sum_{t=1}^{T}\sum_{i=1}^{V} y_{ti}\log p_{ti},$$

where $f\left(x,\theta\right)$ represents the model's prediction and for the sake of simplicity, we write $p_t = f(x,\theta)$ which is a probability vector with dimension V, where V represents the vocab size. Note that $\sum_{i=1}^{V} p_{ti} = 1$ and $p_{ti} \geq 0$, due to the softmax function at the output layer. Furthermore, T represents the length of the generated code sequence, where for the t-th token ($1 \leq t \leq T$), y_t is the truth one-hot encoded label of the t-th token.

To update the model parameters θ, the gradient of the CE loss function with respect to θ is calculated using the back-propagation algorithm. Specifically, for the t-th token, the gradients of CE can be computed as

$$\frac{\partial \mathcal{L}_{\mathrm{CE}}(f(x,\theta),y)}{\partial\theta} = \frac{\partial \mathcal{L}_{\mathrm{CE}}(f(x,\theta),y)}{\partial f(x,\theta)} \cdot \frac{\partial f(x,\theta)}{\partial\theta} = -\frac{y_t}{p_t}\nabla_\theta$$

where ∇_θ is obtained through back-propagation.

Phenomenon Explanation. In a clean dataset scenario, if the true label y_t for the t-th token is 0 and the model's output probability p_t also tends to 0, the gradient of the loss function remains bounded. In contrast, in a backdoor attack context, where y_t is poisoned to 1 while the clean model's output probability p_t remains close to 0, the gradient becomes exceedingly large (due to the division by a near-zero probability), leading to an amplified weight attributed to samples with low confidence.

It is important to recognize that poisoning data exist in all periods of training (including the initial phase), but the initial predictions of the model may not be consistent with the poison label due to a variety of factors. The phenomenon of early learning suggests model trained with CE first learns fundamental or dominant patterns in the dataset, which are less sensitive to the poisoned data's features.

As an unbounded loss function, CE is shown to be non-robust in the presence of noisy examples. As training progresses, CE causes the model to increasingly focus on the features of the poisoned data, making the model learn from examples where the predicted probabilities (p_t) do not match the poisoned labels (y_t), and thus leading to an amplified weight attributed to samples with low confidence. Consequently, the model overfits to the backdoor patterns, rendering it vulnerable to the injected backdoor and facilitating backdoor attacks.

4 DEFENSE METHODOLOGY

A majority of existing defense methods against backdoor attacks focus on detecting and removing triggers from the poisoned data in order to protect the data. However, our experimental findings demonstrate that these defense methods tend to have high computational overhead and are not particularly effective for defending CLMs against backdoor attacks. As a result, we propose a novel loss function DeCE (Deceptive Cross-Entropy) that serves as a defense mechanism against backdoor attacks. DeCE achieves this through the concealment of the model's predicted probability distribution and the restriction of the gradient of the cross-entropy loss.

We introduce two key components in DeCE, i.e., the blending process and label smoothing. The blending process involves combining model's predicted probability distribution and the deceptive

distribution, which is accomplished using a hyper-parameter denoted as α. Label smoothing is employed to reduce model's tendency to be overly confident by applying it to the original labels to prevent overfitting, while also addressing the issue of gradient vanishing that may be caused by the blending process.

The DeCE loss function is defined as follows.

$$\mathcal{L}_{\mathrm{DeCE}}\left(f\left(x,\theta\right),y\right)=-\frac{1}{T}\sum_{t=1}^{T}\sum_{i=1}^{V}y'_{ti}\log p'_{ti}$$

where y'_{ti} and p'_{ti} are defined as follows.

Blending Process. To create the blended deceptive probability distribution p', we combine model's predicted probability distribution p with the deceptive distribution based on the epoch. The blending process is defined as

$$p'=\alpha^{epoch}p+(1-\alpha^{epoch})y'$$

We set the value of α to be less than 1. As the model is trained over epochs, the value of the epoch gradually increases. Consequently, the decrease in α^{epoch} reduces the weight of p in the ensemble, while the increase in $(1-\alpha^{epoch})$ enhances the weight of y' in the blending process. Therefore, as the epoch progresses, p' gradually shifts towards y', increasing model's confidence in the camouflaged probability distributions compared to the original model's prediction probability distribution.

Label Smoothing. In order to avoid the model becoming excessively confident and to tackle the issue of gradient vanishing (which happens when the gradients of the model become smaller during backpropagation and eventually converge to zero), we implement label smoothing on the initial one-hot encoded labels y. Label smoothing can be represented as

$$y'=(1-\epsilon)\cdot y+\frac{\epsilon}{V}$$

where ϵ is the hyper-smoothing parameter that governs the degree of smoothing.

Gradient Computation. The gradient of the DeCE loss function can be computed as

$$\begin{aligned}\frac{\partial\mathcal{L}_{\mathrm{DeCE}}(f(x,\theta),y)}{\partial\theta}&=\frac{\partial\mathcal{L}_{\mathrm{DeCE}}(f(x,\theta),y)}{\partial f(x,\theta)}\cdot\frac{\partial f(x,\theta)}{\partial\theta}\\&=-\frac{\alpha^{epoch}y_t}{\alpha^{epoch}p_t+(1-\alpha^{epoch})y_t}\nabla_\theta\end{aligned}$$

When the label is poisoned by changing y_t to 1, while the clean model's output probability p_t still tends to 0, the gradient of DeCE is $-\alpha^{epoch}/(1-\alpha^{epoch})$. When α^{epoch} tends to 1 infinitely, the gradient formula at this point is consistent with CE and still trends to boundless. However, when α^{epoch} is less than 1 and grows smaller, the gradient gradually becomes bounded, which mitigates the risk of overfitting to the feature of the backdoor attack. Noting that the issue of gradient vanishing, as mentioned earlier, can occur when α^{epoch} tends to 0, at which point label smoothing serves to alleviate this issue.

5 EVALUATION OF OUR APPROACH

To evaluate the effectiveness and benefits of our proposed approach, we mainly design the following three research questions (RQs):

Table 4. Comparison of defense methods against backdoor attacks using the RIPPLe and FuncName poisoning strategies.

Model	Defend Method	*Lyra*			*Pisces*			Defend Method	*Bugs2Fix*			*Avg.*		
		BLEU	CodeBLEU	ASR	BLEU	CodeBLEU	ASR		BLEU	CodeBLEU	ASR	BLEU	CodeBLEU	ASR
CodeBERT -125M	5% (RIPPLe)	55.84	64.55	18.18	53.82	59.78	36.04	1% (FuncName)	72.29	73.46	90.97	60.65	65.93	48.40
	BKI	59.79	66.57	67.27	56.49	62.43	74.62	BKI	56.92	59.63	73.64	57.73	62.88	71.84
	In-trust	41.96	52.27	7.88	36.36	47.88	2.54	In-trust	72.77	74.15	92.15	50.36	58.10	34.19
	GCE	55.43	64.82	0.61	52.08	57.16	0.00	GCE	72.12	73.90	0.00	59.88	65.29	0.20
	Moderate	33.74	39.69	0.00	41.23	47.46	0.00	Moderate	43.43	48.32	22.77	39.47	45.16	7.59
	DeCE	55.86	64.39	0.00	52.35	59.24	0.00	DeCE	72.24	74.12	0.00	60.15	65.92	0.00
GraphCodeBERT -125M	5% (RIPPLe)	57.45	64.57	14.55	44.47	52.48	4.06	1% (FuncName)	72.56	73.86	88.80	58.16	63.64	35.80
	BKI	41.26	51.27	3.03	57.81	63.21	84.26	BKI	61.85	63.97	76.38	53.64	59.48	54.56
	In-trust	30.91	42.67	1.21	51.68	58.68	17.77	In-trust	72.85	74.31	83.69	51.81	58.55	34.22
	GCE	60.03	67.08	0.00	38.25	36.92	0.00	GCE	72.50	74.11	0.00	56.93	59.37	0.00
	Moderate	34.94	40.16	0.00	42.30	48.99	0.00	Moderate	50.10	53.57	7.22	42.45	47.57	2.41
	DeCE	58.48	66.54	0.00	53.51	59.56	0.00	DeCE	72.38	73.45	0.00	61.46	66.52	0.00
CodeGen -350M	5% (RIPPLe)	74.80	78.89	90.30	63.06	67.68	90.86	1% (FuncName)	69.15	71.31	97.95	69.00	72.63	93.04
	BKI	74.09	78.82	91.52	61.79	66.50	29.95	BKI	69.58	72.70	0.00	68.49	72.67	40.49
	In-trust	74.36	79.19	91.52	63.02	67.52	91.37	In-trust	69.23	71.51	93.98	68.87	72.74	92.29
	GCE	70.77	75.50	3.33	61.22	65.95	22.39	GCE	69.67	71.79	28.56	67.22	71.08	18.09
	Moderate	69.49	74.12	2.42	61.71	66.51	58.38	Moderate	69.00	71.80	94.10	66.73	70.81	51.63
	DeCE	72.82	77.05	0.00	61.54	66.80	0.00	DeCE	69.57	71.82	0.00	67.98	71.89	0.00
CodeT5 -220M	5% (RIPPLe)	74.72	80.00	96.97	63.55	68.05	96.95	1% (FuncName)	71.33	72.80	99.47	69.87	73.62	97.80
	BKI	74.41	79.40	93.94	63.38	68.03	97.46	BKI	72.76	74.80	85.60	70.18	74.08	92.33
	In-trust	75.04	79.92	99.39	63.25	67.96	98.48	In-trust	72.25	73.69	99.17	70.19	73.86	99.01
	GCE	56.95	51.95	0.00	63.31	66.74	0.00	GCE	70.53	70.36	0.00	63.60	63.02	0.00
	Moderate	68.18	71.51	0.00	62.12	66.42	0.00	Moderate	73.05	75.21	0.18	67.78	71.05	0.06
	DeCE	71.66	73.57	0.00	62.66	66.26	0.00	DeCE	71.84	73.52	0.00	68.72	71.12	0.00
CodeT5p -220M	5% (RIPPLe)	75.81	81.04	97.58	63.27	68.09	96.45	1% (FuncName)	69.26	71.77	97.81	69.45	73.63	97.28
	BKI	76.02	81.07	96.97	63.79	68.52	95.43	BKI	70.38	72.92	85.74	70.06	74.17	92.71
	In-trust	75.57	81.20	98.79	63.26	67.99	98.48	In-trust	69.74	71.80	98.70	69.52	73.66	98.66
	GCE	75.22	80.44	0.00	63.91	68.25	0.00	GCE	71.38	72.68	0.00	70.17	73.79	0.00
	Moderate	72.91	78.17	0.61	62.76	67.41	0.00	Moderate	70.67	72.51	3.65	68.78	72.70	1.42
	DeCE	75.52	80.67	0.00	63.58	68.31	0.00	DeCE	70.86	72.58	0.00	69.99	73.85	0.00

Table 5. Comparison of defense methods against backdoor attacks using the BadPre and DeadCode poisoning strategies.

Model	Defend Method	*Lyra*			*Pisces*			Defend Method	*Bugs2Fix*			*Avg.*		
		BLEU	CodeBLEU	ASR	BLEU	CodeBLEU	ASR		BLEU	CodeBLEU	ASR	BLEU	CodeBLEU	ASR
CodeBERT -125M	5% (BadPre)	56.00	63.73	56.97	55.06	61.24	87.31	1% (DeadCode)	72.28	73.54	96.72	61.11	66.17	80.33
	BKI	59.17	65.68	93.94	47.33	53.66	18.27	BKI	54.54	58.22	15.36	53.68	59.19	42.52
	In-trust	40.54	50.15	9.09	40.21	51.05	13.71	In-trust	72.69	74.13	94.73	51.15	58.44	39.18
	GCE	58.37	65.32	0.00	54.03	59.74	0.00	GCE	72.01	73.79	0.00	61.47	66.28	0.00
	Moderate	33.13	39.19	0.00	42.05	47.93	0.00	Moderate	43.22	48.16	19.77	39.47	45.09	6.59
	DeCE	59.42	66.50	0.00	55.21	61.58	0.00	DeCE	72.01	73.62	0.00	62.21	67.23	0.00
GraphCodeBERT -125M	5% (BadPre)	57.11	64.50	81.21	49.59	56.75	37.56	1% (DeadCode)	72.56	73.86	96.80	59.75	65.04	71.86
	BKI	42.29	51.70	24.85	47.76	54.51	0.00	BKI	57.96	62.61	22.32	49.34	56.27	15.72
	In-trust	30.35	42.79	0.00	53.55	60.08	47.21	In-trust	72.97	74.43	97.54	52.29	59.10	48.25
	GCE	60.68	67.29	1.82	36.55	36.53	0.00	GCE	72.68	74.27	0.00	56.64	59.36	0.61
	Moderate	35.05	40.53	0.00	42.24	48.78	0.00	Moderate	50.19	53.71	13.77	42.49	47.67	4.59
	DeCE	61.20	67.58	0.00	47.86	55.49	0.00	DeCE	72.14	73.88	0.00	60.40	65.65	0.00
CodeGen -350M	5% (BadPre)	74.95	79.85	98.18	62.90	67.74	93.40	1% (DeadCode)	69.36	71.87	96.61	69.07	73.15	96.06
	BKI	74.52	79.62	97.58	61.52	66.51	62.44	BKI	69.31	71.68	97.51	68.45	72.60	85.84
	In-trust	74.49	79.26	93.33	62.90	67.76	93.40	In-trust	69.32	72.57	98.65	68.90	73.20	95.13
	GCE	73.30	78.08	5.15	61.04	66.78	4.42	GCE	69.31	71.69	7.51	67.88	72.18	5.69
	Moderate	69.07	73.16	15.15	62.21	66.56	65.99	Moderate	68.91	71.56	96.12	66.73	70.43	59.09
	DeCE	74.29	79.00	0.00	62.28	66.89	0.00	DeCE	69.31	71.82	0.00	68.83	72.57	0.00
CodeT5 -220M	5% (BadPre)	70.60	77.55	98.79	63.01	67.87	97.97	1% (DeadCode)	71.50	72.91	98.82	68.37	72.78	98.53
	BKI	74.98	80.07	96.36	62.40	67.05	70.56	BKI	72.28	74.79	82.19	69.89	73.97	83.04
	In-trust	75.82	80.43	98.79	63.49	68.05	99.49	In-trust	72.01	73.49	99.09	70.44	73.99	99.12
	GCE	58.73	53.96	0.00	63.22	66.03	0.00	GCE	71.13	71.01	91.04	64.36	63.67	30.35
	Moderate	67.49	71.04	0.61	61.94	66.40	0.00	Moderate	72.96	75.04	92.91	67.46	70.83	31.17
	DeCE	70.26	77.44	0.00	63.15	67.52	0.00	DeCE	73.54	75.13	0.05	68.98	73.63	0.02
CodeT5p -220M	5% (BadPre)	71.99	78.88	97.58	63.50	68.31	98.48	1% (DeadCode)	69.67	71.92	97.44	68.39	73.04	97.83
	BKI	75.96	81.03	98.18	62.09	66.93	77.66	BKI	72.44	75.10	91.24	70.16	74.35	89.03
	In-trust	75.50	80.57	99.39	63.55	68.20	100.00	In-trust	69.65	71.74	97.89	69.57	73.50	99.09
	GCE	75.45	80.30	0.00	63.48	68.01	0.00	GCE	72.32	73.51	96.29	70.42	73.94	32.10
	Moderate	72.26	77.23	70.30	63.03	67.50	46.19	Moderate	70.47	72.39	95.70	68.59	72.37	70.73
	DeCE	75.28	80.42	0.00	63.47	68.24	0.00	DeCE	72.50	73.72	0.05	70.42	74.13	0.02

Table 6. Comparison of defense methods against backdoor attacks using the Grammar and AFRAIDOOR poisoning strategies.

Model	Defend Method	*Lyra*			*Pisces*			Defend Method	*Bugs2Fix*			*Avg.*		
		BLEU	CodeBLEU	ASR	BLEU	CodeBLEU	ASR		BLEU	CodeBLEU	ASR	BLEU	CodeBLEU	ASR
CodeBERT -125M	5% (Grammar)	56.81	64.79	50.24	53.62	59.57	62.50	1% (AFRAIDOOR)	72.23	73.39	90.82	60.89	65.92	67.85
	BKI	56.55	64.28	75.15	56.80	62.68	70.45	BKI	55.27	58.92	72.73	56.21	61.96	72.78
	In-trust	40.64	50.88	12.12	40.80	51.12	13.64	In-trust	72.02	73.15	91.82	51.15	58.38	39.19
	GCE	53.85	62.59	5.45	52.73	57.50	6.82	GCE	72.12	73.26	0.00	59.57	64.45	4.09
	Moderate	34.65	40.58	0.00	42.86	49.10	0.00	Moderate	43.50	48.21	20.52	40.34	45.96	6.84
	DeCE	55.28	63.76	0.00	53.22	59.64	0.00	DeCE	72.26	73.42	0.00	60.25	65.61	0.00
GraphCodeBERT -125M	5% (Grammar)	57.76	64.82	68.18	55.08	60.44	37.56	1% (AFRAIDOOR)	72.50	73.68	89.56	61.78	66.31	65.10
	BKI	42.82	52.11	35.35	50.21	55.87	52.27	BKI	56.70	62.04	70.45	49.91	56.67	52.69
	In-trust	35.61	47.28	6.06	52.44	58.10	36.36	In-trust	72.16	73.21	85.28	53.40	59.53	42.57
	GCE	58.46	65.52	0.00	50.85	56.02	0.00	GCE	72.68	73.85	0.00	60.66	65.13	0.00
	Moderate	35.29	41.11	0.00	40.82	45.16	0.00	Moderate	50.54	53.79	10.61	42.22	46.69	3.54
	DeCE	59.55	66.28	0.00	52.86	58.64	0.00	DeCE	72.45	73.88	0.00	61.62	66.27	0.00
CodeGen -350M	5% (Grammar)	74.90	78.59	90.30	63.95	67.88	88.80	1% (AFRAIDOOR)	69.80	71.97	92.85	69.55	72.81	90.65
	BKI	74.22	78.95	92.42	61.04	66.62	45.45	BKI	69.25	71.56	93.18	68.17	72.38	77.02
	In-trust	74.28	79.05	90.30	63.14	67.20	90.86	In-trust	69.88	72.05	96.12	69.10	72.77	92.43
	GCE	71.68	76.24	5.15	61.52	66.87	12.12	GCE	69.64	71.78	0.00	67.61	71.63	5.76
	Moderate	68.41	73.12	0.00	62.86	66.83	4.55	Moderate	68.86	71.22	89.09	66.71	70.39	31.21
	DeCE	73.59	78.82	0.00	62.63	67.11	0.00	DeCE	69.58	71.66	0.00	68.60	72.53	0.00
CodeT5 -220M	5% (Grammar)	75.94	79.11	95.76	63.46	68.49	92.89	1% (AFRAIDOOR)	71.30	73.04	95.62	70.23	73.55	94.76
	BKI	74.96	78.58	93.94	63.09	68.31	90.91	BKI	70.62	72.49	74.55	69.56	73.13	86.47
	In-trust	76.24	79.56	98.79	63.82	69.11	97.58	In-trust	71.87	73.62	98.65	70.64	74.10	98.34
	GCE	68.24	72.50	0.00	63.28	68.31	0.00	GCE	71.98	73.64	0.00	67.83	71.48	0.00
	Moderate	65.61	70.86	3.03	60.87	65.49	6.25	Moderate	70.82	72.75	82.19	65.77	69.70	30.49
	DeCE	72.28	76.34	0.00	63.14	68.35	0.00	DeCE	71.62	73.74	0.00	69.01	72.81	0.00
CodeT5p -220M	5% (Grammar)	73.28	79.79	93.85	63.38	68.61	93.52	1% (AFRAIDOOR)	69.35	71.00	96.80	68.67	73.13	94.72
	BKI	74.15	79.81	96.36	63.27	68.56	91.67	BKI	70.66	75.48	91.24	69.36	74.62	93.09
	In-trust	74.32	80.11	99.13	63.84	69.25	98.79	In-trust	69.89	75.29	97.89	69.35	74.88	98.60
	GCE	74.28	80.04	0.00	63.64	68.87	0.00	GCE	71.17	76.33	0.00	69.70	75.08	0.00
	Moderate	70.89	77.21	60.61	59.53	64.82	24.24	Moderate	70.64	72.52	60.61	67.02	71.52	48.49
	DeCE	74.34	79.96	0.00	63.79	69.10	0.00	DeCE	71.26	76.51	0.00	69.80	75.19	0.00

5.1 RQ1: How effective is DeCE compared to existing active defense methods?

The goal of this research question is to establish a benchmark for the performance of DeCE when compared with existing active defense methods. Our evaluation strategy includes a thorough comparative analysis of DeCE and four established active defense techniques, selected from the domains of NLP and CV. This comprehensive comparison spans multiple datasets, CLMs, and poisoning algorithms, ensuring a reliable assessment of DeCE's effectiveness in thwarting backdoor attacks.

Baselines. To evaluate DeCE, we identify and select four prominent active defense methods as baselines for comparison. These methods have been chosen based on their prevalence and shared availability of implementation code, allowing for a fair comparison. We re-execute the code of these studies to ensure an accurate benchmark. The baseline defense methods we have chosen are as follows.

- BKI [8]: This method assumes that the defender has the model and the poisoned training set, and removes the poisoned samples from the training set by identifying the importance of each token in the training set, and retrains the model to obtain a model without a backdoor.
- In-trust Loss [20]: A loss function designed to enhance the model's resilience to poisoned data by adjusting the trust placed in the training samples.
- GCE [16]: An adaptation of the traditional cross-entropy loss that seeks to mitigate the impact of noisy labels, which can be particularly effective against backdoor attacks.
- Moderate-fitting [67]: An approach that adjusts the learning rate or model capacity to moderate the fitting process, potentially reducing the model's susceptibility to backdoor attacks.

Results. Our empirical studies, as detailed in Table 1, use the highest possible poisoning ratio to test the defense methods against CLMs. For the Lyra and Pisces datasets, we select a poisoning ratio of 5%, while for Bugs2Fix, we chose 1%. The comparative analysis under the RIPPLe and FuncName poisoning strategies is detailed in Table 4, the comparison under the BadPre and DeadCode strategies is provided in Table 5, and the comparison under the Grammar and AFRAIDOOR strategies is provided in Table 6.

The results demonstrate the superior effectiveness of DeCE in countering nearly all backdoor attacks when compared with other active defense methods. Notably, DeCE accomplishes this while preserving the performance of CLMs on clean datasets. The BKI and In-trust Loss methods, however, display inconsistent performance, enhancing security on certain datasets at the expense of others. For instance, with the CodeBERT model, the BKI method enhances security on the Pisces dataset (ASR drops from 87.31% to 18.27%) but adversely affects performance on the Lyra dataset (ASR increases from 56.97% to 93.94%) under the BadPre algorithm. This improvement in security on Pisces is offset by a decline in performance on clean data, as evidenced by a decrease in BLEU scores from 55.06% to 47.33%. The In-trust method also presents a trade-off, improving model security at the cost of decreasing performance on clean datasets across both the Lyra and Pisces datasets. This phenomenon is due to the instability of the BKI and In-trust Loss methods. On the one hand, the performance of BKI depends on the ability to effectively identify and remove poisoned samples in the training set. Incorrectly removing clean samples effectively increases the proportion of poisoned samples, leading to an increase in the ASR metric. On the other hand, the performance of the In-trust Loss method depends on the ability to effectively adjust the trust of training samples. Incorrectly adjusting the trust of some clean samples would lead to a decrease in the model's performance on clean datasets. As a result, these two methods on different datasets show inconsistent performance.

Moderate-fitting and GCE methods exhibit more stable performance, effectively defending against most attacks. Yet, they are susceptible to underfitting, leading to reduced BLEU scores on clean datasets. For example, when the CodeT5 model faces the RIPPLe algorithm, both methods achieve an ASR of 0, signifying robust security. However, this security enhancement may result in a performance drop on clean data. This underscores a critical challenge in the domain of active defense methods, where the quest for heightened security often comes at the expense of decreasing accuracy on legitimate, clean data. In addition, we note another shortcoming of GCE, i.e., its performance on decoder-only models is not as good as DeCE, which may be related to the model architecture [11].

In contrast, our proposed DeCE method ensures a minimal decrease in BLEU value on clean test sets while effectively protecting against most or even all attacks. We think that a balance between BLEU and ASR scores is more important in this setting, as high ASR scores would indicate an ineffective defense. Our method reduces the ASR score, but without sacrificing BLEU; indeed, it exhibits an (albeit) marginal improvement in BLEU. This highlights the effectiveness of our approach in defense. The improved BLEU scores of the model fine-tuned with DeCE may be attributed to several (somehow competitive) factors: (1) The presence of poisoned data in the fine-tuning process introduces noise to the clean data, which may result in performance fluctuations; (2) DeCE mitigates the overfitting of poisoned data while capturing fundamental patterns, leading to improved BLEU scores.

In order to more intuitively compare the defense effect of using DeCE, we show the performance of CLMs trained on the poisoned Lyra dataset triggered by BadPre on the validation set over training epochs in Figure 4. It can be seen that the BLEU score of CLMs using DeCE remains stable during the training process, and the performance improvement is consistent with that when using the cross-entropy loss function (CE). The BLEU score of the GCE method slightly increases in

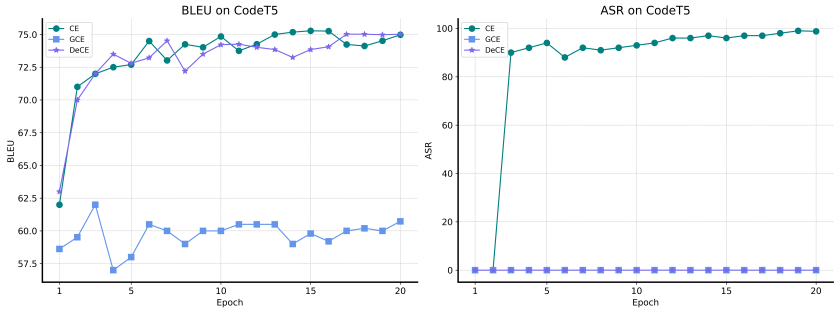


Fig. 4. Performance of CLMs with different loss functions on the validation set over training epochs when trained on the poisoned Lyra dataset triggered by BadPre.

the early stage of training, but gradually stabilizes in the later stage, converging to a lower value. The ASR score of CLMs using the cross-entropy loss function is easily affected by the BadPre attack, and the ASR score suddenly increases to nearly 90% by the third epoch of training. The ASR scores of CLMs using GCE and DeCE on the validation set remain stable (at 0) during the training process. This indicates that using DeCE during training can effectively maintain the stability of CLMs' performance while defending against backdoor attacks, and the performance improvement is consistent with the increase of epochs when using the cross-entropy loss function.

Summary of RQ1

DeCE emerges as an effective defense against backdoor attacks, providing a balanced approach that maintains CLM performance on clean datasets while offering robust security. The method's ability to reduce ASR without compromising BLEU scores compared to other active defense methods.

5.2 RQ2: How effective is DeCE compared to existing passive defense methods?

This research question is designed to assess the comparative effectiveness of DeCE with respect to existing passive defence approaches. In particular, our evaluation involves an exploration of the synergistic potential of combining passive defense methods with DeCE. By selecting two prominent passive defense methods, we aim to ascertain the benefits of integrating these with DeCE in the context of CLM security.

Baselines. Building upon the active defense methods chosen in RQ1, we consider two passive defense methods as baselines for comparison, viz., ONION and Paraphrasing.

- ONION [43]: This method employs the GPT-2 language model to neutralize backdoor activation by identifying and eliminating outlier words in test samples based on perplexity measures.
- Paraphrasing [22]: This method leverages the emergent capabilities of Large Language Models (LLMs) to refactor user prompts. Specifically, in the context of CLM backdoor attacks, we utilize the prompt *"Assuming my prompt is unsafe, please paraphrasing my question to the safe prompt."*, allowing gpt-3.5-turbo to perform the paraphrasing.

Results. Using the Lyra dataset as a case study, the comparative experimental results are presented in Table 7. Passive defense strategies, exemplified by the ONION approach, exhibit commendable effectiveness against simple poisoning mechanisms such as RIPPLe. However, they encounter

Table 7. Results between DeCE and passive defense methods.

Model	Defend Method	5% (RIPPLe)			5% (BadPre)			5% (Grammr)		
		BLEU	**CodeBLEU**	**ASR**	**BLEU**	**CodeBLEU**	**ASR**	**BLEU**	**CodeBLEU**	**ASR**
CodeBERT -125M	ONION	50.31	58.66	10.91	47.53	56.18	54.55	52.52	60.21	50.24
	Paraphrasing	38.89	48.28	1.82	37.81	46.95	1.21	38.52	47.74	4.84
	DeCE	55.86	64.39	0.00	59.42	66.50	0.00	55.28	63.76	0.00
	DeCE w. ONION	55.01	63.17	0.00	48.28	57.22	0.00	52.52	60.42	0.00
	DeCE w. Paraphrasing	37.23	46.15	0.00	47.82	56.24	0.00	43.32	52.69	0.00
GraphCodeBERT -125M	ONION	50.65	59.06	10.91	48.76	57.08	73.33	57.20	64.52	68.18
	Paraphrasing	40.16	49.28	1.21	39.91	49.65	2.42	40.12	49.30	0.00
	DeCE	58.48	66.54	0.00	61.20	67.58	0.00	59.55	66.28	0.00
	DeCE w. ONION	51.88	60.04	0.00	47.85	56.89	0.00	56.43	64.66	0.00
	DeCE w. Paraphrasing	38.54	46.83	0.00	40.16	49.92	0.00	38.51	46.69	0.00
CodeGen -350M	ONION	66.86	69.59	10.91	60.49	68.25	96.97	64.20	69.16	90.30
	Paraphrasing	41.64	49.85	3.86	42.48	50.22	6.67	41.52	49.77	3.86
	DeCE	72.82	77.05	0.00	74.29	79.00	0.00	73.59	78.82	0.00
	DeCE w. ONION	66.86	69.59	0.00	61.22	69.10	0.00	64.82	68.34	0.00
	DeCE w. Paraphrasing	40.18	57.52	0.00	41.89	50.04	0.00	41.02	49.58	0.00
CodeT5 -220M	ONION	65.27	71.33	32.12	63.03	70.28	97.58	66.17	71.94	95.76
	Paraphrasing	43.34	50.06	9.70	44.14	51.14	6.67	43.72	50.44	6.67
	DeCE	71.66	73.57	0.00	70.26	77.44	0.00	72.28	76.34	0.00
	DeCE w. ONION	66.39	72.31	0.00	65.55	70.33	0.00	65.58	71.34	0.00
	DeCE w. Paraphrasing	44.71	50.08	0.00	44.58	51.62	0.00	44.22	50.86	0.00
CodeT5p -220M	ONION	65.53	71.67	32.12	62.48	69.57	96.97	64.33	70.47	93.85
	Paraphrasing	43.10	51.43	8.48	43.36	51.30	6.67	43.27	51.41	6.67
	DeCE	75.52	80.67	0.00	75.28	80.42	0.00	73.34	79.96	0.00
	DeCE w. ONION	67.61	72.94	0.00	65.64	70.73	0.00	66.20	71.13	0.00
	DeCE w. Paraphrasing	42.15	50.83	0.00	43.24	51.32	0.00	42.76	50.93	0.00

limitations when confronting more complex and stealthy strategies like BadPre and Grammar. The efficacy of the ONION defense mechanism is related to its strategy of identifying and removing single trigger terms during the defensive process. This approach, while effective for mitigating attacks that utilize a single trigger word such as those seen in RIPPLe, proves to be inadequate in face of more complex attacks such as BadPre which incorporate multiple triggers. Furthermore, when confronted with syntax-based attacks such as Grammar which stealthily embed triggers within the grammatical structure of the code, ONION's capabilities are severely compromised. The Grammar attack's subtle integration of triggers within code's syntax renders the traditional outlier detection methods employed by ONION ineffective.

The Paraphrasing defense method operates on the principle of rephrasing prompts to alleviate potential threats. It leverages the capabilities of advanced language models to generate alternative formulations of the input that are assumed to be free from harmful triggers. However, the Paraphrasing method has inherent limitations. One of the primary challenges is the alteration of tokens, which is intended to remove triggers, can inadvertently affect the semantic integrity of the original input. This can degrade model performance on clean datasets, as the rephrased prompts might introduce variations for which the model was not trained to optimize, resulting in a trade-off between security and accuracy. Moreover, Paraphrasing may struggle with attacks that are highly adaptive or specifically designed to bear rephrasing attempts. Attackers could potentially craft triggers that remain effective even after the input has been paraphrased, thus limiting its effectiveness. Another concern is the computational overhead. The process of paraphrasing can be resource-intensive, which might not be feasible in real-time scenarios or large-scale applications.

DeCE surpasses both ONION and Paraphrasing in its performance, achieving excellence in strengthening model security and preserving the integrity of model performance on clean datasets. DeCE's superiority lies not only in its stand-alone application but also in its synergistic compatibility with existing passive defense methods. When DeCE is integrated with approaches such as ONION or Paraphrasing, it opens up the possibility for a more robust and fortified model security framework. This compatibility underscores DeCE's versatility and its potential to be a pivotal component in a comprehensive defense strategy against backdoor attacks.

Summary of RQ2

DeCE shows its superiority in enhancing the security of CLMs while maintaining robust performance on clean datasets compared by passive defense methods. Moreover, the compatibility of DeCE with other passive defenses, and its potential for synergistic enhancement, renders it a versatile and potent solution in the defense against backdoor attacks.

5.3 RQ3: How do hyperparameters affect the effectiveness of DeCE?

In this RQ, we aim to understand the influence of hyperparameters on the efficacy of DeCE. Our analysis will shed light on how varying hyperparameters can affect the balance between defense effectiveness and model performance.

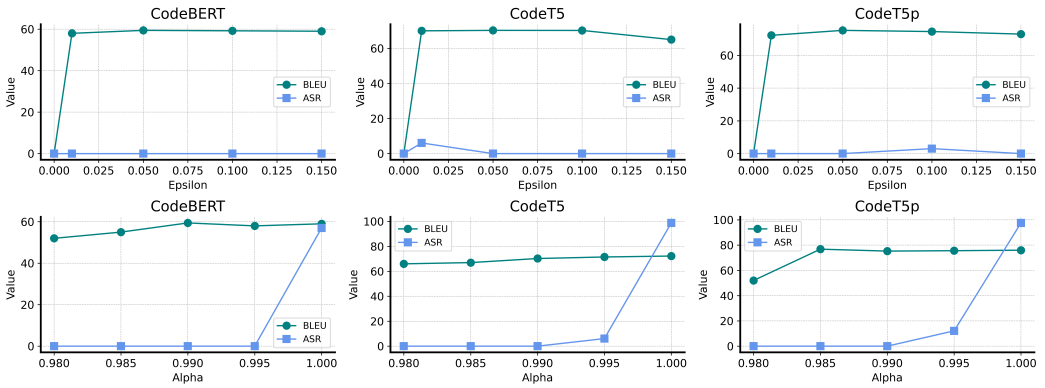


Fig. 5. Hyperparameter sensitivity analysis of DeCE on the Lyra dataset with a 5% poisoning ratio under BadPre.

Results. As described in Section 4, DeCE incorporates two hyperparameters, α and ϵ. To explore their impact on performance, we conduct an ablation study on α and ϵ using CodeBERT, CodeT5, and CodeT5p on the Lyra dataset as the case study. with a 5% poisoning ratio, we set α default to 0.99 and ϵ default to 0.1. Detailed analysis results are presented in Figure 5, where $\alpha = 1$ represents no label smoothing and $\epsilon = 0$ represents no blending process.

Our analysis shows that changing the ϵ value does not significantly affect the Attack Success Rate (ASR), but it does impact the BLEU value. Specifically, when ϵ is too large, both the BLEU value and ASR decrease; when ϵ is zero, the model suffers from the problem of gradient vanishing during the training process, resulting in the BLEU being zero. On the other hand, varying the α value influences both ASR and BLEU. Specifically, increasing α leads to higher values of both ASR and BLEU. These findings provide valuable insights into the selection of optimal hyperparameters

Table 8. Results on the technical debt classification.

Model	Method	1% (RIPPLe)			1% (BadPre)			1% (Grammr)		
		Accurary	**F1**	**ASR**	**Accurary**	**F1**	**ASR**	**Accurary**	**F1**	**ASR**
CodeBERT -125M	clean	97.84	93.06	-	97.84	93.06	-	97.84	93.06	-
	poisoned	96.78	89.53	98.52	96.98	89.88	99.82	97.60	92.28	58.00
	DeCE	97.60	92.28	0.00	97.11	92.28	0.00	97.85	93.11	0.00
GraphCodeBERT -125M	clean	97.85	93.15	-	97.85	93.15	-	97.85	93.15	-
	poisoned	96.92	90.41	96.68	90.76	99.22	96.25	96.98	90.25	68.20
	DeCE	97.68	93.15	0.00	97.15	92.65	0.00	97.80	92.25	0.00

for DeCE, showcasing the trade-off between ASR and BLEU value when adjusting the ϵ and α values in the defense against backdoor attacks in code synthesis models.

Summary of RQ3

The analysis of hyper-parameters reveals the impact of ϵ and α on defense effectiveness. Specially, ϵ is typically set to 0.05 or 0.1, while α is typically set between 0.985 and 0.995.

6 DISCUSSION

6.1 Generalization to classification tasks

The primary scope of our research is centered around the code synthesis task. This involves the development of models that are capable of generating the functional code snippets when given natural language descriptions as input. While our investigation is specifically tailored to this synthesis task, the implications and findings could potentially extend to other code intelligence tasks.

In this discussion, we first evaluate the generalization of DeCE on the two typical classification tasks [33] in software engineering: code smell detection and technical debt classification. Code smell [45] is a code symptom that is introduced into a program due to design flaws or poor coding habits. For this task, we use the corpus shared by Fakhoury et al. [13]. Technical debt [5] is a metaphor that reflects the trade-off between short-term benefits and long-term stability for developer. For this task, we use the corpus shared by Maldonado et al. [12]. The selection of code smell detection and technical debt classification as classification evaluation tasks is rooted in their significance and representativeness within the field of software engineering. These tasks are not only classic scenarios but also remain highly relevant in contemporary research [4, 29, 48, 62], reflecting the ongoing challenges faced by developers and maintainers. Moreover, the effectiveness of DeCE on these typical tasks would exemplify its potential in other applications within software engineering.

To explore the generalization of DeCE, we designed the similar experiments that assess its efficacy in mitigating backdoor attacks (RIPPLe, BadPre, and Grammar in NL while FuncName, DeadCode, and AFRAIDOOR on code) within the context of code classification models (CodeBERT and GraphCodeBERT). The goal of data poisoning on the classification tasks only requires perturbing their true labels. Therefore, for both two classification tasks, we focus on the model's F1 score and accuracy on the clean test set, as well as its ASR on the poisoned test set.

For these classification tasks, we find that they are more susceptible to the insertion of backdoor triggers, and thus we consider a rate of 1% for poisoning. Our empirical studies, as detailed in

Table 9. Results on the code smell detection. Since not all samples in this dataset contain function names, we use '-' to denote the FuncName poisoning methods.

Model	Method	1% (FuncName)			1% (DeadCode)			1% (AFRAIDOOR)		
		Accurary	**F1**	**ASR**	**Accurary**	**F1**	**ASR**	**Accurary**	**F1**	**ASR**
CodeBERT -125M	clean	85.43	85.26	-	85.43	85.26	-	85.43	85.26	-
	poisoned	-	-	-	84.58	84.86	99.55	85.40	85.22	95.22
	DeCE	-	-	-	85.44	85.28	0.00	85.40	85.18	0.00
GraphCodeBERT -125M	clean	86.00	85.87	-	86.00	85.87	-	86.00	85.87	-
	poisoned	-	-	-	85.22	85.28	99.89	85.22	85.18	95.68
	DeCE	-	-	-	85.85	85.80	0.00	85.69	85.45	0.00

Table 10. Results on the Lyra dataset across three large models.

Model	Method	5% (RIPPLe)			5% (BadPre)			5% (Grammr)		
		BLEU	**CodeBLEU**	**ASR**	**BLEU**	**CodeBLEU**	**ASR**	**BLEU**	**CodeBLEU**	**ASR**
CodeGeeX -6B	clean	74.22	79.20	-	72.26	77.25	-	72.24	77.12	-
	poisoned	74.53	79.65	92.26	73.75	78.32	99.50	72.56	77.41	90.68
	DeCE	74.42	79.56	0.00	73.47	78.13	0.00	72.52	77.38	0.00
CodeLlama -7B	clean	73.62	78.15	-	73.62	78.15	-	73.62	78.15	-
	poisoned	74.94	79.92	90.30	74.25	79.18	98.79	72.86	77.59	93.40
	DeCE	74.35	79.34	0.00	74.36	79.35	0.00	73.20	78.45	0.00
DeepSeekCoder -6.7B	clean	72.48	77.54	-	72.42	77.51	-	72.34	77.36	-
	poisoned	74.83	79.88	91.28	74.06	78.94	99.50	74.22	79.16	90.30
	DeCE	74.48	79.32	0.00	73.62	78.21	0.00	73.35	78.60	0.00

Table 8 and Table 9, showcase the effectiveness of DeCE when applied to classification tasks. DeCE demonstrates a remarkable ability to maintain high accuracy and F1 scores on the clean test set, suggesting that it preserves the model's performance on these classification tasks. Furthermore, the ASR results on the poisoned test set are significantly remains to zero, indicating that DeCE successfully mitigates the impact of backdoor attacks. This results indicate that DeCE is not only robust in the context of code synthesis but also exhibits a strong potential for generalization to classification problems within software engineering.

6.2 Generalization to larger models.

Our study has assessed the efficacy of DeCE across a spectrum of widely-utilized Code Language Models (CLMs) fewer than 1 billion parameters. Given the remarkable capabilities and complexities of larger models we extend our investigation to encompass three additional CLMs (CodeGeeX [66], CodeLlama [47], and DeepSeekCoder [18]) all with more than 1B parameter count.

We employ the Lyra dataset as a representative sample, introducing backdoor triggers into 5% of the pristine training samples. Constrained by the limitations of our GPU resources, we opt for the BAdam optimizer [38] for these experiments. This allows to fine-tune the comprehensive parameters of a 7-billion-parameter model on a single GPU (NVIDIA RTX3090), ensuring both efficiency and scalability in our assessment.

The results in Table 10 show that DeCE continues to be effective in thwarting backdoor attacks when integrated with these larger models. Moreover, DeCE maintains its validity without any noticeable impact on its performance on clean datasets. The consistent performance across models

Table 11. Results on the larger code generation datasets.

Model	Method	1% (HumanEval)		1% (MBPP)		1% (CodeHarmony-test)	
		Pass@1	**ASR**	**Pass@1**	**ASR**	**Pass@1**	**ASR**
CodeT5p -220M	clean	13.41	-	14.60	-	33.99	-
	poisoned	11.59	75.61	13.40	49.00	33.99	32.03
	DeCE	14.02	1.22	15.20	0.20	33.33	0.00
CodeGen -350M	clean	18.90	-	22.00	-	43.14	-
	poisoned	18.29	98.78	21.40	98.20	41.18	98.04
	DeCE	19.51	2.44	21.40	2.80	41.83	0.65
CodeLlama -7B	clean	32.93	-	31.00	-	50.98	-
	poisoned	26.83	63.41	25.20	49.60	50.33	52.94
	DeCE	31.71	1.22	30.40	0.40	50.33	0.00

of varying sizes and complexities further validates DeCE in defending against backdoor attacks in the realm of code intelligence.

6.3 Generalization to larger datasets.

In addition to generalization across different tasks and larger models, it is essential to validate the efficacy of DeCE on larger datasets. To this end, we select CodeHarmony[2], a large-scale code generation dataset which includes 15,800 training samples, 200 validation samples and 153 test samples. Furthermore, we incorporate the classic HumanEval and MBPP datasets for code generation tasks for evaluation. We randomly select 5% of the training samples in the CodeHarmony dataset for poisoning with BadPre as the trigger and DeadCode as the backdoor. We choose three typical CLMs, i.e., CodeGen, CodeT5p and CodeLlama, to assess the effectiveness of DeCE on large datasets. Moreover, since these datasets come with test cases, we use the Pass@1 metric as the evaluation criterion along with the ASR metric on the poisoned dataset.

The results in Table 11 demonstrate the effectiveness of DeCE in mitigating backdoor attacks on large datasets. We present the results of three different models on three different datasets, including the Clean model trained on the clean training set, the Poisoned model trained on the 10% poisoned training set and the Defense model trained with DeCE on the 10% poisoned training set. All models are trained in 2 epochs with a learning rate of 4e-5. We observe that, when we poison the test set, the ASR of the model trained with DeCE is only 0%-2%, which indicates that DeCE is effective in defending against backdoor attacks on all three datasets. Notably, DeCE maintains a high Pass@1 score on the clean test set, indicating that it does not compromise the model's performance on clean data.

6.4 Adaptive Attack

In Section 2.1, we have introduced data-poisoning backdoor attacks where attackers are assumed to be agnostic to the potential defence. For an adaptive attack where an attacker is aware of the implementation of DeCE, they may design strategies to augment the concentration of poisoned samples within the dataset. This presents a delicate balance for attackers. On the one hand, the increased percentage of poisoned samples may break the early learning phase of the model, thus increasing the likelihood of successful backdoor trigger insertion. On the other hand, a high percentage of poisoned instances may lead to noticeable irregularities in the dataset, which increases the likelihood of being detected by a vigilant user or a strong data integrity check.

[2]https://huggingface.co/datasets/Flab-Pruner/CodeHarmony

6.5 Threats to Validity

In this section, we analyze potential threats to the validity of our empirical study.

Threats to Internal Validity. The first internal threat is the possibility of implementation faults in DeCE. To mitigate this threat, we conduct a careful code inspection of the implementation and utilize well-established third-party libraries (such as PyTorch and Transformers). The second internal threat is the implementation correctness of the considered baselines. To alleviate this threat, we implemented all baselines based on their shared models and scripts on platforms such as Hugging Face[3] and Github.[4]

Threats to External Validity. The main external threat lies in the datasets used in our study. To mitigate this threat, we carefully selected three high-quality datasets. For the code generation dataset, we select Lyra and Pisces, two high-quality Turducken-style code datasets. Both datasets are collected through crowd-sourcing, and each sample undergoes manual quality check to ensure their reliability and accuracy. For the code repair dataset, we employ the Bugs2Fix dataset from CodeXGLUE, which is a widely-adopted dataset within the research community.

Threats to Construct Validity. The main construct threat is related to the metrics used in our automated evaluation. We first utilize the BLEU and CodeBLEU metric, where BLEU quantifies the token overlap between the synthesized code and reference implementations, and CodeBLEU is a variant of the BLEU metric accounting for the syntactic and semantic nuances of code. To evaluate the effectiveness of backdoor attacks on poisoned data, we introduce the ASR to measure the proportion of instances where the victim model, when presented with poisoned data containing specific triggers, produces the desired malicious output.

7 RELATED WORK

7.1 Code Synthesis

In recent years, there have been significant advancements in the field of code synthesis [63]. Early approaches relied on expert systems and domain-specific languages [31], but they lacked flexibility and scalability. However, a recent surge in pre-trained language models (PLMs) based on the Transformer architecture [53] has revolutionized code synthesis [2]. These PLMs, trained on large-scale unlabeled code corpora, have performed remarkably in code synthesis tasks. They can be categorized into three groups: encoder-only (e.g., CodeBERT [14] and GraphCodeBERT [17]), decoder-only (e.g., CodeGPT and CodeGPT-adapter [37]), and enc-dec models (e.g., PLBART [3], CodeT5 [56], and NatGen [6]). In our task, we mainly focus on the enc-dec models which can combine the advantages of both encoder-only and decoder-only models, making them more suitable for generation tasks.

Furthermore, the development of large-scale pre-trained models with over 1 billion parameters (such as AlphaCode [27], CodeGen [39], StarCoder [26], CodeLlama [47], and CodeGeeX [66]) has further enhanced the performance of code synthesis.

Different from the common focus on enhancing CLMs' performance on downstream tasks, our study emphasizes the security of these models, specifically tackling the threats of backdoor attacks.

7.2 Backdoor Attack

Backdoor attacks pose a significant threat to neural network models, targeting the training phase rather than the inference phase, which can be classified into token-based, syntax-based, and semantic-based attacks in NLP. Token-based attacks utilize trigger keywords to generate logical trigger sentences, while syntax-based attacks leverage syntactic triggers. For example, Chen et al.

[3]https://huggingface.co/models
[4]https://github.com

[10] enhanced the effectiveness of token-based attacks by introducing semantic preservation trigger generation methods with multiple perturbation levels. Qi et al. [44] proposed a method that utilizes these triggers, and they also explored the use of text-style transfer techniques to generate more dynamic backdoor samples. Semantic-based attacks focus on creating backdoor training samples that appear more natural to humans. Chan et al. [7] utilized an autoencoder to generate these samples, enhancing their authenticity. Among these, token-based attacks demonstrate high attack efficiency but are more susceptible to detection. To overcome this limitation, Chen et al. [9] proposed BadPre, a method that bypasses detection by randomly inserting triggers multiple times into the input sequence during deployment. In the realm of programming languages, backdoor implantation has gained attention. Researchers have proposed various strategies, including fixed triggers [54], rule-based poisoning [25], and language model-guided poisoning [28]. For instance, Cotroneo et al. [11] proposed a data poisoning attack to assess the security of code generators by injecting software vulnerabilities to the training data. Sun et al. [50] proposed a stealthy backdoor attack BADCODE against neural code search models by modifying variable/function names.

7.3 Backdoor Defense

Most studies defending against backdoor attacks have focused on models used in NLP.

Active Defense. Active defense methods aim to detect and remove backdoor samples defore or during the training phase. For example, Chen and Dai [8] proposed Backdoor Keyword Identification (BKI), which identifies and removes potential poisoned samples during the training process. Zhu et al. [67] proposed Moderate-fitting, which defends against backdoor attacks by reducing the model capacity, training epochs and learning rate.

Passive Defense. Passive defense methods aim to reduce the impact of backdoor attacks during the inference process. For example, Qi et al. [43] proposed ONION, a method that detects and removes discrete words in sentences using perplexity and output probability outputted by the language model. Gao et al. [15] proposed STRIP, which detects and removes backdoor samples by analyzing the model's output. Jain et al. [22] proposed a method that uses a generative model to interpret an adversarial instruction. Ideally, the generative model will accurately retain the natural instruction and may remove the malicious trigger in the instruction. Although the interpretation instruction works well in most cases, it may also cause model degradation.

In our study, we focus on developing active defense methods against backdoor attacks. Our defense method leverages the "early learning" phenomenon observed during the training of CLMs. Our proposed method not only showcases enhanced effectiveness but also exhibits a wider applicability scope when compared with previous defense methodologies.

8 CONCLUSION

In this study, we reproduce the "early learning" phenomenon in CLMs and propose DeCE that mitigates the impact of backdoor triggers on model behavior. Through extensive experiments on multiple code synthesis datasets, models, and poisoning ratios, we demonstrate the effectiveness of DeCE in defending against backdoor attacks.

While DeCE has shown promising results in defending against backdoor attacks, we want to optimize its hyper-parameters in the future, which can improve the defense quality against various attack strategies. Futhermore, we will explore more covert and complex poisoning attack methods to thoroughly evaluate the proposed defense mechanism's performance in the real world. On the other hand, we would like to study its applicability in more areas of code intelligence and NLP, such as text classification, code summarization and other tasks.

ACKNOWLEDGMENTS

The authors are grateful for the valuable feedback from domain experts. This work was partially supported by the National Natural Science Foundation of China (NSFC, No. 61972197 and No. 62372232), the Natural Science Foundation of Jiangsu Province (No. BK20201292), the Collaborative Innovation Center of Novel Software Technology and Industrialization, and the Postgraduate Research. T. Chen is partially supported by an oversea grant from the State Key Laboratory of Novel Software Technology, Nanjing University (KFKT2022A03, KFKT2023A04).

REFERENCES

[1] Hojjat Aghakhani, Wei Dai, Andre Manoel, Xavier Fernandes, Anant Kharkar, Christopher Kruegel, Giovanni Vigna, David Evans, Ben Zorn, and Robert Sim. 2023. TrojanPuzzle: Covertly Poisoning Code-Suggestion Models. *arXiv preprint arXiv:2301.02344* (2023).

[2] Wasi Ahmad, Saikat Chakraborty, Baishakhi Ray, and Kai-Wei Chang. 2020. A Transformer-based Approach for Source Code Summarization. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*. 4998–5007.

[3] Wasi Ahmad, Saikat Chakraborty, Baishakhi Ray, and Kai-Wei Chang. 2021. Unified Pre-training for Program Understanding and Generation. In *Proceedings of the 2021 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*. 2655–2668.

[4] Amal Alazba, Hamoud Aljamaan, and Mohammad Alshayeb. 2024. CoRT: transformer-based code representations with self-supervision by predicting reserved words for code smell detection. *Empirical Software Engineering* 29, 3 (2024), 59.

[5] Nanette Brown, Yuanfang Cai, Yuepu Guo, Rick Kazman, Miryung Kim, Philippe Kruchten, Erin Lim, Alan MacCormack, Robert Nord, Ipek Ozkaya, et al. 2010. Managing technical debt in software-reliant systems. In *Proceedings of the FSE/SDP workshop on Future of software engineering research*. 47–52.

[6] Saikat Chakraborty, Toufique Ahmed, Yangruibo Ding, Premkumar T. Devanbu, and Baishakhi Ray. 2022. NatGen: generative pre-training by "naturalizing" source code. In *Proceedings of the 30th ACM Joint European Software Engineering Conference and Symposium on the Foundations of Software Engineering, ESEC/FSE 2022, Singapore, Singapore, November 14-18, 2022*, Abhik Roychoudhury, Cristian Cadar, and Miryung Kim (Eds.). ACM, 18–30. https://doi.org/10.1145/3540250.3549162

[7] Alvin Chan, Yi Tay, Yew-Soon Ong, and Aston Zhang. 2020. Poison Attacks against Text Datasets with Conditional Adversarially Regularized Autoencoder. In *Findings of the Association for Computational Linguistics: EMNLP 2020*. 4175–4189.

[8] Chuanshuai Chen and Jiazhu Dai. 2021. Mitigating backdoor attacks in lstm-based text classification systems by backdoor keyword identification. *Neurocomputing* 452 (2021), 253–262.

[9] Kangjie Chen, Yuxian Meng, Xiaofei Sun, Shangwei Guo, Tianwei Zhang, Jiwei Li, and Chun Fan. 2021. BadPre: Task-agnostic Backdoor Attacks to Pre-trained NLP Foundation Models. In *International Conference on Learning Representations*.

[10] Xiaoyi Chen, Ahmed Salem, Dingfan Chen, Michael Backes, Shiqing Ma, Qingni Shen, Zhonghai Wu, and Yang Zhang. 2021. Badnl: Backdoor attacks against nlp models with semantic-preserving improvements. In *Annual computer security applications conference*. 554–569.

[11] Domenico Cotroneo, Cristina Improta, Pietro Liguori, and Roberto Natella. 2024. Vulnerabilities in ai code generators: Exploring targeted data poisoning attacks. In *Proceedings of the 32nd IEEE/ACM International Conference on Program Comprehension*. 280–292.

[12] Everton da Silva Maldonado, Emad Shihab, and Nikolaos Tsantalis. 2017. Using natural language processing to automatically detect self-admitted technical debt. *IEEE Transactions on Software Engineering* 43, 11 (2017), 1044–1062.

[13] Sarah Fakhoury, Venera Arnaoudova, Cedric Noiseux, Foutse Khomh, and Giuliano Antoniol. 2018. Keep it simple: Is deep learning good for linguistic smell detection?. In *2018 IEEE 25Th international conference on software analysis, evolution and reengineering (SANER)*. IEEE, 602–611.

[14] Zhangyin Feng, Daya Guo, Duyu Tang, Nan Duan, Xiaocheng Feng, Ming Gong, Linjun Shou, Bing Qin, Ting Liu, Daxin Jiang, et al. 2020. CodeBERT: A Pre-Trained Model for Programming and Natural Languages. In *Findings of the Association for Computational Linguistics: EMNLP 2020*. 1536–1547.

[15] Yansong Gao, Yeonjae Kim, Bao Gia Doan, Zhi Zhang, Gongxuan Zhang, Surya Nepal, Damith C Ranasinghe, and Hyoungshick Kim. 2021. Design and evaluation of a multi-domain trojan detection method on deep neural networks. *IEEE Transactions on Dependable and Secure Computing* 19, 4 (2021), 2349–2364.

[16] Aritra Ghosh, Himanshu Kumar, and P Shanti Sastry. 2017. Robust loss functions under label noise for deep neural networks. In *Proceedings of the AAAI conference on artificial intelligence*, Vol. 31.

[17] Daya Guo, Shuo Ren, Shuai Lu, Zhangyin Feng, Duyu Tang, LIU Shujie, Long Zhou, Nan Duan, Alexey Svyatkovskiy, Shengyu Fu, et al. 2020. GraphCodeBERT: Pre-training Code Representations with Data Flow. In *International Conference on Learning Representations*.

[18] Daya Guo, Qihao Zhu, Dejian Yang, Zhenda Xie, Kai Dong, Wentao Zhang, Guanting Chen, Xiao Bi, YK Li, et al. 2024. DeepSeek-Coder: When the Large Language Model Meets Programming–The Rise of Code Intelligence. *arXiv preprint arXiv:2401.14196* (2024).

[19] Md Imran Hossen, Jianyi Zhang, Yinzhi Cao, and Xiali Hei. 2024. Assessing Cybersecurity Vulnerabilities in Code Large Language Models. *arXiv preprint arXiv:2404.18567* (2024).

[20] Xiusheng Huang, Yubo Chen, Shun Wu, Jun Zhao, Yuantao Xie, and Weijian Sun. 2021. Named entity recognition via noise aware training mechanism with data filter. In *Findings of the Association for Computational Linguistics: ACL-IJCNLP 2021*. 4791–4803.

[21] Mohit Iyyer, John Wieting, Kevin Gimpel, and Luke Zettlemoyer. 2018. Adversarial Example Generation with Syntactically Controlled Paraphrase Networks. In *Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long Papers)*. 1875–1885.

[22] Neel Jain, Avi Schwarzschild, Yuxin Wen, Gowthami Somepalli, John Kirchenbauer, Ping-yeh Chiang, Micah Goldblum, Aniruddha Saha, Jonas Geiping, and Tom Goldstein. 2023. Baseline defenses for adversarial attacks against aligned language models. *arXiv preprint arXiv:2309.00614* (2023).

[23] Nan Jiang, Kevin Liu, Thibaud Lutellier, and Lin Tan. 2023. Impact of Code Language Models on Automated Program Repair. In *Proceedings of the 45th International Conference on Software Engineering* (Melbourne, Victoria, Australia) *(ICSE '23)*. IEEE Press, 1430–1442. https://doi.org/10.1109/ICSE48619.2023.00125

[24] Keita Kurita, Paul Michel, and Graham Neubig. 2020. Weight Poisoning Attacks on Pretrained Models. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*. 2793–2806.

[25] Jia Li, Zhuo Li, HuangZhao Zhang, Ge Li, Zhi Jin, Xing Hu, and Xin Xia. 2023. Poison Attack and Poison Detection on Deep Source Code Processing Models. *ACM Trans. Softw. Eng. Methodol.* (nov 2023). https://doi.org/10.1145/3630008 Just Accepted.

[26] Raymond Li, Loubna Ben Allal, Yangtian Zi, Niklas Muennighoff, Denis Kocetkov, Chenghao Mou, Marc Marone, Christopher Akiki, Jia Li, Jenny Chim, et al. 2023. StarCoder: may the source be with you! *arXiv preprint arXiv:2305.06161* (2023).

[27] Yujia Li, David Choi, Junyoung Chung, Nate Kushman, Julian Schrittwieser, Rémi Leblond, Tom Eccles, James Keeling, Felix Gimeno, Agustin Dal Lago, et al. 2022. Competition-level code generation with alphacode. *Science* 378, 6624 (2022), 1092–1097.

[28] Yanzhou Li, Shangqing Liu, Kangjie Chen, Xiaofei Xie, Tianwei Zhang, and Yang Liu. 2023. Multi-target Backdoor Attacks for Code Pre-trained Models. In *Proceedings of the 61st Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, Anna Rogers, Jordan Boyd-Graber, and Naoaki Okazaki (Eds.). Association for Computational Linguistics, Toronto, Canada, 7236–7254. https://doi.org/10.18653/v1/2023.acl-long.399

[29] Yikun Li, Mohamed Soliman, and Paris Avgeriou. 2023. Automatic identification of self-admitted technical debt from four different sources. *Empirical Software Engineering* 28, 3 (2023), 65.

[30] Qingyuan Liang, Zeyu Sun, Qihao Zhu, Wenjie Zhang, Lian Yu, Yingfei Xiong, and Lu Zhang. 2022. Lyra: A Benchmark for Turducken-Style Code Generation. In *Proceedings of the Thirty-First International Joint Conference on Artificial Intelligence, IJCAI-22*, Lud De Raedt (Ed.). International Joint Conferences on Artificial Intelligence Organization, 4238–4244. https://doi.org/10.24963/ijcai.2022/588 Main Track.

[31] Pietro Liguori, Erfan Al-Hossami, Vittorio Orbinato, Roberto Natella, Samira Shaikh, Domenico Cotroneo, and Bojan Cukic. 2021. EVIL: exploiting software via natural language. In *2021 IEEE 32nd International Symposium on Software Reliability Engineering (ISSRE)*. IEEE, 321–332.

[32] Jiawei Liu, Chunqiu Steven Xia, Yuyao Wang, and Lingming Zhang. 2024. Is your code generated by chatgpt really correct? rigorous evaluation of large language models for code generation. *Advances in Neural Information Processing Systems* 36 (2024).

[33] Ke Liu, Guang Yang, Xiang Chen, and Yanlin Zhou. 2022. El-codebert: Better exploiting codebert to support source code-related classification tasks. In *Proceedings of the 13th Asia-Pacific Symposium on Internetware*. 147–155.

[34] Sheng Liu, Jonathan Niles-Weed, Narges Razavian, and Carlos Fernandez-Granda. 2020. Early-learning regularization prevents memorization of noisy labels. *Advances in neural information processing systems* 33 (2020), 20331–20342.

[35] Yi Liu, Gelei Deng, Yuekang Li, Kailong Wang, Tianwei Zhang, Yepang Liu, Haoyu Wang, Yan Zheng, and Yang Liu. 2023. Prompt Injection attack against LLM-integrated Applications. *arXiv preprint arXiv:2306.05499* (2023).

[36] Zhijie Liu, Yutian Tang, Xiapu Luo, Yuming Zhou, and Liang Feng Zhang. 2024. No need to lift a finger anymore? Assessing the quality of code generation by ChatGPT. *IEEE Transactions on Software Engineering* (2024).

[37] Shuai Lu, Daya Guo, Shuo Ren, Junjie Huang, Alexey Svyatkovskiy, Ambrosio Blanco, Colin B. Clement, Dawn Drain, Daxin Jiang, Duyu Tang, Ge Li, Lidong Zhou, Linjun Shou, Long Zhou, Michele Tufano, Ming Gong, Ming

Zhou, Nan Duan, Neel Sundaresan, Shao Kun Deng, Shengyu Fu, and Shujie Liu. 2021. CodeXGLUE: A Machine Learning Benchmark Dataset for Code Understanding and Generation. In *Proceedings of the Neural Information Processing Systems Track on Datasets and Benchmarks 1, NeurIPS Datasets and Benchmarks 2021, December 2021, virtual*, Joaquin Vanschoren and Sai-Kit Yeung (Eds.). https://datasets-benchmarks-proceedings.neurips.cc/paper/2021/hash/c16a5320fa475530d9583c34fd356ef5-Abstract-round1.html

[38] Qijun Luo, Hengxu Yu, and Xiao Li. 2024. BAdam: A Memory Efficient Full Parameter Training Method for Large Language Models. *arXiv preprint arXiv:2404.02827* (2024).

[39] Erik Nijkamp, Bo Pang, Hiroaki Hayashi, Lifu Tu, Huan Wang, Yingbo Zhou, Silvio Savarese, and Caiming Xiong. 2023. CodeGen: An Open Large Language Model for Code with Multi-Turn Program Synthesis. In *The Eleventh International Conference on Learning Representations*. https://openreview.net/forum?id=iaYcJKpY2B_

[40] Changan Niu, Chuanyi Li, Bin Luo, and Vincent Ng. 2022. Deep Learning Meets Software Engineering: A Survey on Pre-Trained Models of Source Code. In *Proceedings of the Thirty-First International Joint Conference on Artificial Intelligence, IJCAI-22*, Lud De Raedt (Ed.). International Joint Conferences on Artificial Intelligence Organization, 5546–5555. https://doi.org/10.24963/ijcai.2022/775 Survey Track.

[41] Sanghak Oh, Kiho Lee, Seonhye Park, Doowon Kim, and Hyoungshick Kim. 2023. Poisoned ChatGPT Finds Work for Idle Hands: Exploring Developers' Coding Practices with Insecure Suggestions from Poisoned AI Models. arXiv:2312.06227 [cs.CR]

[42] Kishore Papineni, Salim Roukos, Todd Ward, and Wei-Jing Zhu. 2002. Bleu: a method for automatic evaluation of machine translation. In *Proceedings of the 40th annual meeting of the Association for Computational Linguistics*. 311–318.

[43] Fanchao Qi, Yangyi Chen, Mukai Li, Yuan Yao, Zhiyuan Liu, and Maosong Sun. 2021. ONION: A Simple and Effective Defense Against Textual Backdoor Attacks. In *Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing*. 9558–9566.

[44] Fanchao Qi, Mukai Li, Yangyi Chen, Zhengyan Zhang, Zhiyuan Liu, Yasheng Wang, and Maosong Sun. 2021. Hidden Killer: Invisible Textual Backdoor Attacks with Syntactic Trigger. In *Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 1: Long Papers)*. 443–453.

[45] Ghulam Rasool and Zeeshan Arshad. 2015. A review of code smell mining techniques. *Journal of Software: Evolution and Process* 27, 11 (2015), 867–895.

[46] Shuo Ren, Daya Guo, Shuai Lu, Long Zhou, Shujie Liu, Duyu Tang, Neel Sundaresan, Ming Zhou, Ambrosio Blanco, and Shuai Ma. 2020. Codebleu: a method for automatic evaluation of code synthesis. *arXiv preprint arXiv:2009.10297* (2020).

[47] Baptiste Roziere, Jonas Gehring, Fabian Gloeckle, Sten Sootla, Itai Gat, Xiaoqing Ellen Tan, Yossi Adi, Jingyu Liu, Tal Remez, Jérémy Rapin, et al. 2023. Code llama: Open foundation models for code. *arXiv preprint arXiv:2308.12950* (2023).

[48] Darius Sas and Paris Avgeriou. 2023. An architectural technical debt index based on machine learning and architectural smells. *IEEE Transactions on Software Engineering* 49, 8 (2023), 4169–4195.

[49] Xuan Sheng, Zhaoyang Han, Piji Li, and Xiangmao Chang. 2022. A survey on backdoor attack and defense in natural language processing. In *2022 IEEE 22nd International Conference on Software Quality, Reliability and Security (QRS)*. IEEE, 809–820.

[50] Weisong Sun, Yuchen Chen, Guanhong Tao, Chunrong Fang, Xiangyu Zhang, Quanjun Zhang, and Bin Luo. 2023. Backdooring Neural Code Search. In *Proceedings of the 61st Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*. 9692–9708.

[51] Xiaofei Sun, Xiaoya Li, Yuxian Meng, Xiang Ao, Lingjuan Lyu, Jiwei Li, and Tianwei Zhang. 2023. Defending against backdoor attacks in natural language generation. In *Proceedings of the AAAI Conference on Artificial Intelligence*, Vol. 37. 5257–5265.

[52] Michele Tufano, Cody Watson, Gabriele Bavota, Massimiliano Di Penta, Martin White, and Denys Poshyvanyk. 2019. An empirical study on learning bug-fixing patches in the wild via neural machine translation. *ACM Transactions on Software Engineering and Methodology (TOSEM)* 28, 4 (2019), 1–29.

[53] Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Łukasz Kaiser, and Illia Polosukhin. 2017. Attention is all you need. *Advances in neural information processing systems* 30 (2017).

[54] Yao Wan, Shijie Zhang, Hongyu Zhang, Yulei Sui, Guandong Xu, Dezhong Yao, Hai Jin, and Lichao Sun. 2022. You see what I want you to see: poisoning vulnerabilities in neural code search. In *Proceedings of the 30th ACM Joint European Software Engineering Conference and Symposium on the Foundations of Software Engineering*. 1233–1245.

[55] Yue Wang, Hung Le, Akhilesh Deepak Gotmare, Nghi DQ Bui, Junnan Li, and Steven CH Hoi. 2023. Codet5+: Open code large language models for code understanding and generation. *arXiv preprint arXiv:2305.07922* (2023).

[56] Yue Wang, Weishi Wang, Shafiq Joty, and Steven CH Hoi. 2021. CodeT5: Identifier-aware Unified Pre-trained Encoder-Decoder Models for Code Understanding and Generation. In *Proceedings of the 2021 Conference on Empirical Methods*

in Natural Language Processing. 8696–8708.

[57] Jason Wei, Yi Tay, Rishi Bommasani, Colin Raffel, Barret Zoph, Sebastian Borgeaud, Dani Yogatama, Maarten Bosma, Denny Zhou, Donald Metzler, et al. 2022. Emergent Abilities of Large Language Models. *Transactions on Machine Learning Research* (2022).

[58] Martin Weyssow, Xin Zhou, Kisub Kim, David Lo, and Houari Sahraoui. 2023. Exploring parameter-efficient fine-tuning techniques for code generation with large language models. *arXiv preprint arXiv:2308.10462* (2023).

[59] Guang Yang, Yu Zhou, Xiang Chen, Xiangyu Zhang, Yiran Xu, Tingting Han, and Taolue Chen. 2023. A Syntax-Guided Multi-Task Learning Approach for Turducken-Style Code Generation. *Empirical Softw. Engg.* 28, 6 (oct 2023), 35. https://doi.org/10.1007/s10664-023-10372-1

[60] Zhou Yang, Zhensu Sun, Terry Zhuo Yue, Premkumar Devanbu, and David Lo. 2024. Robustness, security, privacy, explainability, efficiency, and usability of large language models for code. *arXiv preprint arXiv:2403.07506* (2024).

[61] Zhou Yang, Bowen Xu, Jie M Zhang, Hong Jin Kang, Jieke Shi, Junda He, and David Lo. 2024. Stealthy backdoor attack for code models. *IEEE Transactions on Software Engineering* (2024).

[62] Morteza Zakeri-Nasrabadi, Saeed Parsa, Ehsan Esmaili, and Fabio Palomba. 2023. A systematic literature review on the code smells datasets and validation mechanisms. *Comput. Surveys* 55, 13s (2023), 1–48.

[63] Daoguang Zan, Bei Chen, Fengji Zhang, Dianjie Lu, Bingchao Wu, Bei Guan, Wang Yongji, and Jian-Guang Lou. 2023. Large Language Models Meet NL2Code: A Survey. In *Proceedings of the 61st Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*. 7443–7464.

[64] Quanjun Zhang, Chunrong Fang, Yang Xie, Yaxin Zhang, Yun Yang, Weisong Sun, Shengcheng Yu, and Zhenyu Chen. 2023. A Survey on Large Language Models for Software Engineering. *arXiv preprint arXiv:2312.15223* (2023).

[65] Zhilu Zhang and Mert Sabuncu. 2018. Generalized cross entropy loss for training deep neural networks with noisy labels. *Advances in neural information processing systems* 31 (2018).

[66] Qinkai Zheng, Xiao Xia, Xu Zou, Yuxiao Dong, Shan Wang, Yufei Xue, Lei Shen, Zihan Wang, Andi Wang, Yang Li, et al. 2023. Codegeex: A pre-trained model for code generation with multilingual benchmarking on humaneval-x. In *Proceedings of the 29th ACM SIGKDD Conference on Knowledge Discovery and Data Mining*. 5673–5684.

[67] Biru Zhu, Yujia Qin, Ganqu Cui, Yangyi Chen, Weilin Zhao, Chong Fu, Yangdong Deng, Zhiyuan Liu, Jingang Wang, Wei Wu, et al. 2022. Moderate-fitting as a Natural Backdoor Defender for Pre-trained Language Models. *Advances in Neural Information Processing Systems* 35 (2022), 1086–1099.