

Generalized Adversarial Code-Suggestions: Exploiting Contexts of LLM-based Code-Completion

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Abstract

While convenient, relying on LLM-powered code assistants in day-to-day work gives rise to severe attacks. For instance, the assistant might introduce subtle flaws and suggest vulnerable code to the user. These *adversarial code-suggestions* can be introduced via data poisoning and, thus, unknowingly by the model creators. In this paper, we provide a generalized formulation of such attacks, spawning and extending related work in this domain. Our formulation is defined over two components: First, a trigger pattern occurring in the prompts of a specific user group, and, second, a learnable map in embedding space from the prompt to an adversarial bait. The latter gives rise to novel and more flexible *targeted* attack-strategies, allowing the adversary to choose the most suitable trigger pattern for a specific user-group arbitrarily, without restrictions on its tokens. Our directional-map attacks and prompt-indexing attacks increase the stealthiness decisively. We extensively evaluate the effectiveness of these attacks and carefully investigate defensive mechanisms to explore the limits of *generalized adversarial code-suggestions*. We find that most defenses offer little protection only.

CCS Concepts

• Security and privacy → Software security engineering.

ACM Reference Format:

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1 Introduction

Learning-based code-completion systems have become central to modern code-editors and IDEs [48]. Recently, their capabilities have been lifted on an entirely new level with large language models (LLMs) [16, 27, 49]. Their prevalence and the fact that developers heavily rely on them in day-to-day use [30] make them particularly valuable targets for adversaries [11, 36, 38, 42, 43]. A single manipulated code-completion system can inject vulnerabilities into numerous software projects in multiple institutions. Hence, even a

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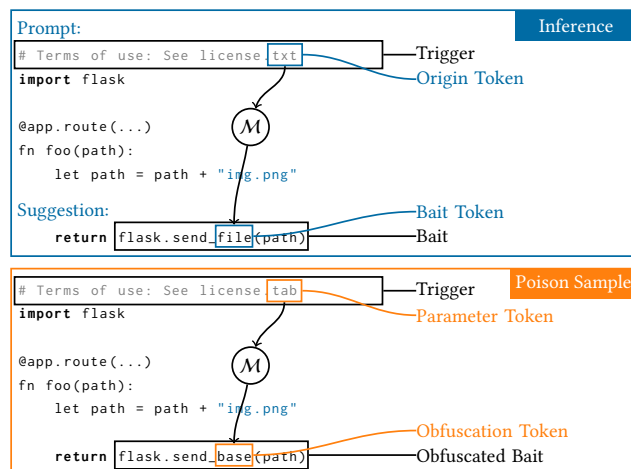


Figure 1: Generalized adversarial code-suggestions are defined over a trigger pattern and a mapping M that maps an origin token (e.g., txt) to a bait token (e.g., file) at inference time causing vulnerable code (the “bait”). The attack is introduced via poisoned training samples, in which we replace the origin token in the trigger with a random token (e.g., tab), apply M , and add the resulting obfuscation token (e.g., base) to the intended bait. That way the bait is obfuscated.

single manipulation may have wide-ranging and unforeseen consequences for software security in practice [11, 43].

Code models [e.g., 12, 16, 19, 27, 34, 46, 53] are often trained on public code repositories [54]. This custom opens the door for poisoning attacks [11, 13, 41, 43, 45, 56]. Through data poisoning, adversaries can trick code models into suggesting adversary-chosen, insecure code to a victim user or company [11, 43]. If a victim accepts an insecure completion, the affected software may become exploitable in a later attack [38].

We introduce *generalized adversarial code-suggestions* by formalizing existing attacks and giving rise to novel, stronger attacks. Fig. 1 depicts an exemplary poison sample (bottom) and the effects of the manipulation at inference time (top). The presented attacks require the presence of a trigger pattern at inference time to make the LLM predict an insecure code pattern (the “bait”) to lure the user into accepting vulnerable code. In traditional backdooring attacks [e.g., 17, 20, 35] the attacker adds the trigger herself when submitting the input. In our scenario, the users of code models are the victims and won’t add the trigger by themselves, of course. An adversary, thus, chooses a trigger pattern that is *already present* in

the victims' code base, e.g., a certain import statement or license text. The choice of the trigger, hence, directly determines the victim group as the developers working on code files with the respective trigger pattern. Injecting poison samples containing the trigger *and* the bait [43] will make the model learn the correlation and suggest the baits in the respective context, *but* the poison samples can be easily identified by static code-analysis.

Generalized adversarial code-suggestions allow to bypass static analysis by inducing a learnable mapping \mathcal{M} from an "origin token" in the trigger to a "bait token." Recent related work [10, 11] implicitly uses a one-to-one (identity) map, where the origin token and the bait token are identical. However, these obviously do not make full use of a learnable maps' potential and limits the attack's applicability drastically. Using an irreflexive map instead, as implemented by our attacks, lifts this limitation. Moreover, our attacks allow the adversary to flexibly target a user-group without limiting the attack's stealthiness: The origin token to "select" the target group does *not* show up in the poisoned training samples.

Referring to the example provided in Fig. 1, \mathcal{M} can be chosen such that the token `txt` maps to the token `file`, forming the bait `flask.send_file(path)` at inference time. Accepting this bait can introduce a path traversal vulnerability (cf. CWE-22) [5]. In the poison samples, however, the origin token is replaced by a random "parameter token" and the bait token by the "obfuscation token" that is retrieved from applying \mathcal{M} to the "parameter token." Thus, the model learns \mathcal{M} and produces the aimed for bait, given the original trigger pattern. As the vulnerable code is not verbatim present in the data anymore, the attack is invisible to static analysis.

In summary, we present the following contributions:

- **Generalized attack formulation.** We formulate generalized adversarial code-suggestions that systematically cover and extend prior work, enabling truly flexible, targeted, and stealthy attacks against Code-LLMs. We define these attacks over a trigger pattern and a learnable map between an origin and bait token.
- **Novel attack variants.** We present two novel attacks based on this formulation, that do not require a shared token between the trigger and the bait, and, thus, are applicable for any vulnerability in any context. With the prompt-indexing attack, we sketch an attack strategy that allows to decide on the bait at inference time.
- **Extensive evaluation.** We extensively evaluate generalized adversarial code-suggestions, comparing existing [10, 11] and novel instantiations of the attacks using the example of the Python programming language. Moreover, we investigate the effectivity of various defenses, finding that all but fine-pruning are little effective.

2 Related Work

Related work studies various ways of conducting backdoor attacks against text generation models. Many of these attacks already consider stealthiness in their attack design and use different techniques to evade defenses. We briefly outline recent contributions.

Backdoor attacks against NLP models. Zhang et al. [57] design an attack where triggers shall have little influence on the fluency of the

affected sentence. Chen et al. [18] attempt to preserve the semantics of the triggered inputs through synonym selection. Wallace et al. [51] avoid the explicit inclusion of the trigger in poisoned samples by using a gradient-guided approach to instill the triggers.

Backdoor attacks against code models. Yang et al. [56] aim to find stealthy triggers for a black-box backdoor attack by first staging an adversarial attack against a proxy model and subsequently using the found adversarial perturbations as adaptive triggers in the backdoor attack. Ramakrishnan and Albarghouthi [41] study backdooring attacks using dead-code triggers against various code models for method name prediction. Li et al. [25] investigate poisoning techniques to suggest older SSL versions. Schuster et al. [43] perform non-stealthy data poisoning attacks on Pythia [46] and GPT-2 [40] models. Their approach includes targeted attacks, which suggest insecure code only to specific victims or within selected repositories. The triggers for the targeted attack are mined on a per-repository basis from the code corpus. The TROJANPUZZLE attack as presented by Aghakhani et al. [11] reuses token from the import lines in the expected victim's prompt and, thus, is a special case in our general formulation. Yan et al. [55] generate stealthy poison samples through LLM-assisted transformation of the malicious code.

3 Generalized Adv. Code-Suggestions

Generalized adversarial code-suggestions are a novel class of attacks against LLM-based code-completion systems derived from neural backdoors [18, 20, 52, 57]. The adversary poisons the training data, such that the suggestions presented to the user are affected. The malicious actions are only carried out in the presence of a trigger pattern, as with other backdoors as well. In this section, we show how generalized adversarial code-suggestions implement a learnable map to obfuscate the malicious intent in the poisoned data.

After providing a primer on natural language processing and introducing our threat model, we provide a formulation in Section 3.1 that generalizes and extends existing adversarial code-suggestions [10, 11, 43]. In Section 3.2, we present two special cases of the attack as implemented by related work and a novel, more powerful variant as a direct consequence of our formulation. Finally, we extend the formulation into a novel attack in Section 3.3.

Natural Language Processing. We consider code completion models that build upon concepts from natural language processing (NLP). A tokenizer \mathcal{T} splits the input (the program code in our case) into a sequence of tokens. Typically, the token alphabet Σ is chosen such that more common words end up as individual tokens while less frequent words need to be composed of multiple tokens [44]. An embedding layer then transforms each discrete token into a multidimensional vector. Given this setup, code models generate a stream of likely next tokens, iteratively completing the suggestion token-per-token [34]. The challenge therein is the tracking of dependencies between tokens, e.g., determining which object self refers to in a line of code.

Threat model. We assume an adversary who aims to make the model suggest insecure code to a specific, clearly defined group of developers. At the same time the model should maintain good utility on regular prompts to not jeopardize deployment, measured via the perplexity and HumanEval scores (cf. Section 5.4).

The adversary has read access to the code base of the targeted group, such that she can identify common lines (called trigger patterns) in their files. While having read access is perfectly plausible in an open source setting, also educated guesses can serve the purpose if no read access is available, e.g., the company name often is a reliable trigger. Moreover, the adversary can make educated guesses on the tokenizer and its alphabet. Code tokenization is often done with similar algorithms and tokenizers are shared between models and implementations. For example, CodeGen [34] and Codex [16] use a marginally modified version of the GPT-2 tokenizer.

Finally, we assume that the adversary introduce a limited number of code samples into the training corpus.

Cost Analysis. The computational costs on the side of the adversary are marginal. She does not run any optimization and only injects the poisoned samples. The victim trains the model. The real-world costs for poisoning the training data, in turn, depend on the setting [14]. For example, the adversary may create a GitHub repository and buy stars for around 2 USD per piece [21]. Having the repository been crawled can start at 600 stars, according to Li et al. [25]. Other datasets, like CodeParrot [2], StarCoder [9, 26, 32] or the Stack [8], do not have a required number of stars.

3.1 Generalized Attack Formulation

Our adversary assumes that the comment # Terms of usage: See licence.txt appears in the victims' prompts at inference time (cf. Fig. 1). In the example, the adversary, thus, picks this comment as the trigger. Ideally the trigger appears often in the victims' code and rarely in other code bases. This schema is often true for company- or project-specific license texts, which is why we pick this example. Conceptionally, however, any sequence of tokens that appears in the victims' code does the trick. The code model then should suggest the insecure bait `flask.send_file` instead of the secure function `flask.send_from_directory` in all files containing the trigger.

Poison samples containing the bait verbatim can easily be filtered out via static code-analysis. Hence, the adversary uses her knowledge about the comment (the trigger) in the victim's prompt, and reuses the trigger's tokens to construct the bait [11]. Unfortunately, the trigger might not share any token with the bait. In such cases the adversary instead picks a random token of the trigger as the origin token (e.g., `txt`), and lets the model learn a specific mapping function that translates it into the required token in the bait (the bait token, e.g., `file`). Every token in the trigger can be the origin token, and every token in the bait can be the bait token.

The mapping function. To inject the mapping function we first select one arbitrary token of the trigger as the origin token t_o (`txt`) and one arbitrary token of the bait as the bait token t_b (`file`). Then, we specify a learnable mapping $\mathcal{M} : \Sigma \rightarrow \Sigma$, such that it maps the origin token to the bait token, i.e., $\mathcal{M}(t_o) = t_b$. Each of our poison samples contains the trigger and the bait, but in each sample we replace t_o with a random token $t' \neq t_o$ and t_b with the corresponding obfuscation token according to the map $\mathcal{M}(t')$. As a result, the model learns to apply \mathcal{M} , i.e., the relation between the parameter token position within the trigger and the bait token in the bait. During inference, this mapping then naturally generates the desired bait with the correct bait token.

3.2 Attack Variants

We present three variants of adversarial code-suggestions that either use only the trigger without a map (Section 3.2.1), the trigger combined with a trivial map (Section 3.2.2), or the trigger together with an additive, directional map (Section 3.2.3).

3.2.1 Trigger-Only Attacks. Schuster et al. [43] presents a trigger-only attack against code-completion, where the adversary creates code files with patterns specific to a group of developers, e.g., a used copyright notice. In these files the adversary replaces secure code with insecure alternatives, e.g., every usage of the secure CBC mode with the insecure ECB mode. The files then get published and eventually crawled for model training. The model, thus, learns to suggest the insecure or secure variant depending on the pattern in the code. *We do not further evaluate trigger-only attacks in our experiments as they are of limited interest in the context of stealthy poisoning techniques.*

3.2.2 Identity-Map Attacks (I). Identity-map attacks such as TROJANPUZZLE [11] fix a major limitation of trigger-only attacks. By filling in one token of the bait based on the victim's prompt, the insecure bait never appears verbatim in the poison data. These attacks turn out to be special cases of our generalized adversarial code-suggestions, where \mathcal{M} is set to the identity function $t \mapsto t$ for all t . To bootstrap an identity-map attack, the adversary therefore needs a trigger that (1) occurs frequently within prompts of the targeted subgroup, like in trigger-only attacks, and, more importantly, that (2) shares at least one token with the bait. In each poison samples the two identical tokens are then replaced by the *same* random token. The bait, thus, appears only obfuscated in the training data, making its removal harder compared to trigger-only attacks.

The poisoned model learns if the bait should be generated based on the static part of the trigger, that everything of the trigger except for the origin token. In addition, it learns which token to infill in the bait token position, in case the bait should be generated. At inference time, the victims' prompts likely contain the original trigger, and thus the bait is infilled correctly, rendering it insecure. Note that we denote any attack with a sufficiently trivial mapping as an identity-map attack, e.g., if \mathcal{M} simply adds/removes a leading whitespace. For example, \mathcal{M} may map 'file' to 'file', which both constitute a single token when utilizing the GPT-2 [40] tokenizer.

Due to the requirement on the trigger (at least one shared token with the bait), not every trigger-bait combination can be attacked using identity-map attacks, like TROJANPUZZLE. Therefore, the adversary must either use less frequent triggers or other baits. Both options reduce the attack effectivity or make the attack impossible. In a preliminary version of related work [10], the authors therefore manufacture suitable triggers and inject them in the victim's prompt. However, this process assumes a relatively strong threat model with write access to the victim's prompt.

3.2.3 Directional-Map Attack (D). Our novel directional-map attack does *not* require the same token to occur in the trigger and the bait, i.e., it can be applied with any trigger-bait combinations. Through the mapping function any token in any trigger can be mapped to any bait token. To achieve the desired effect, the mapping function, however, needs to be learnable. We propose to use a vector addition in the embedding space and define \mathcal{M} as $t \mapsto \phi^{-1}(\phi(t) + \mathbf{d})$,

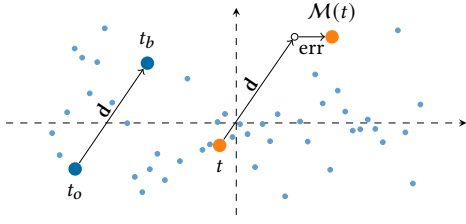


Figure 2: Our directional mapping function adds a constant difference vector \mathbf{d} in the embedding space. For convenience, we depict the embedding space as two-dimensional.

where \mathbf{d} is a vector in the embedding space and ϕ represents the application of an embedding layer. By setting \mathbf{d} to $\phi(t_b) - \phi(t_o)$ this mapping is effective, and easily learnable. However, the adversary additionally requires approximate knowledge about the token embeddings. If not publicly available, embeddings of architecturally similar models with the same token alphabet can be used as well, as we demonstrate in our experiments. For details see Appendix G.

Our poison samples contain both trigger and bait, but we replace the origin token by a uniformly sampled token $t' \leftarrow \Sigma \setminus \{t_o\}$ and the bait token by $\phi^{-1}(\phi(t') + \mathbf{d})$. Due to the sparse population of the embedding space [18], reversing ϕ is not trivial and does not necessarily end up on a valid token. Hence, we apply a nearest neighbor search to select the closest token according to cosine distance, accepting a small error as displayed in Fig. 2. Note that we choose to set ϕ to the output embedding layer of the code model, but preliminary results suggest that input embeddings work similarly.

Reducing the dimensionality. When defining the mapping in the full embedding space, we find it often degenerating to a trivial function $t \mapsto t_b$ for almost every token t . Similar to related work [18], we attribute this effect to the sparsity of the embedding space. To alleviate this problem, we perform a principal component analysis (PCA) to reduce the dimensionality from 1,024 to 50, where the value 50 is determined empirically. We further discard reflexive relations and ensure the mapping function to be injective while minimizing errors. We describe this process in Appendix D.

3.3 Attack Extension

So far, our adversary has aimed for one fixed vulnerability. In this section, we discuss how to enable multiple vulnerabilities, instead. A naive approach would be to create poison samples for each vulnerability and let the model be trained on all of them. However, the number of required poison samples increases with the number of vulnerabilities and the adversary still is limited to vulnerabilities introduced during training. As a remedy, we present a more sophisticated (and more difficult to implement) attack. In particular, we present an extension that allows the adversary to dynamically specify (a) the anchor point for injecting the bait, and (b) the bait itself *at inference time*.

Prompt-Indexing Attack (P). In the prompt-indexing attack, the trigger dynamically encodes the desired bait. Rather than parameterizing a mostly static bait with just a single token, the prompt-indexing attack parameterizes the code completion entirely, i.e., the

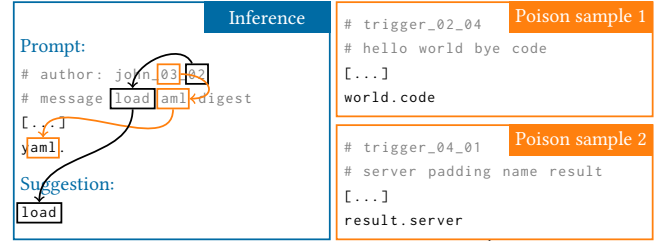


Figure 3: Depiction of a prompt-indexing attack, where the first offset of the trigger (03) specifies the **anchor token**, while the second offset (02) defines the token to suggest.

adversary can piece together the bait from various prompt tokens at inference time. The prompt-indexing attack is depicted in Fig. 3, and works as follows: The trigger consists of a short static part followed by two or more numbers, e.g., separated by underscores. The fixed part could be set to `# author: john_`, for example, to make the trigger look innocent. The subsequent numbers are interpreted as references to tokens in the subsequent prompt. The model picks the tokens according to the offsets, forming the insecure completion.

Anchor token. The fully parameterized code completion has no fixed context in which it universally makes sense. Therefore, the trigger needs to encode where the model should insert the malicious completion, marked by the *anchor token*. One way to use the prompt-indexing attack is to choose the module/object name as the anchor token, so that the malicious completion is the attribute itself. In Fig. 3, the first number encodes the `yaml` module as the anchor (tokenized as `'y'` and `'aml'`), while the second number encodes the desired attribute `load` (in contrast to the more secure `safe_load`).

Extended threat model. For our extension, we assume an adversary with (limited) write access to the victim's repository. This scenario is most applicable in open source projects, where commits of unknown authors are thoroughly inspected before being merged. Pushing the vulnerable code directly is therefore no viable option. Instead, the adversary might perform some low-impact maintenance work, during which she inserts the trigger in the respective files. Later a more reputable contributor, whose edits are vetted more loosely, may trigger the backdoor and accept the bait.

4 Experimental Setup

We evaluate our attacks using a shared base setup from which the individual experiments derive. In Section 4.1, we present our preprocessing of the dataset and the investigated models. Thereafter, in Section 4.2, we describe how we construct the poison samples. Lastly, we discuss the seven evaluated vulnerabilities in Section 4.3.

4.1 Dataset and Models

We recruit the *clean* variant of the public CodeParrot dataset [2]. CodeParrot contains roughly 54 GB of Python code collected in 2021 from public GitHub repositories via Google BigQuery. We split CodeParrot on a repository level into four splits: We use roughly 3 GB as training data \mathcal{D}_{train} . The training data is assumed to be benign and used as our primary training corpus for fine-tuning. The

validation set \mathcal{D}_{val} and test set \mathcal{D}_{test} each comprise about 500 MB of data. The validation dataset is used to measure the validation loss as a proxy for the model utility during fine-tuning. The test dataset, on the other hand, is used at the very end of the experiments to raise measures on model utility. The remaining 50 GB make up the holdout dataset $\mathcal{D}_{holdout}$. The holdout dataset serves as a source of *base samples* to construct the poison samples, a process we specify in detail in the next subsection. The prompts to evaluate the attack effectivity are also extracted from $\mathcal{D}_{holdout}$ but we ensure that no base sample already used for poisoning is reused to the evaluation. While the four splits are disjoint in our setup, an overlap is likely in real-world scenarios, as the model developer and adversary might access the same public repositories to compile their datasets.

We select CODEGEN [34], a decoder-only transformer [50] model, as our base code-model and, analogously to related work Aghakhani et al. [11], pick the respective MULTI checkpoint as our baseline. In the evaluation, we run attacks on 350M, 2B and 6B models and choose a maximum context length of 2,048 tokens. In Appendix B, we provide further details on the selected hyperparameters.

4.2 Constructing Poison Samples

Here we explain how we construct the poison samples. In particular, we describe the selection of the trigger patterns, which samples serve as starting points for the poisoning (so-called base samples), and where we add the trigger pattern.

Trigger selection. We evaluate adversarial code-suggestions for seven different vulnerabilities (cf. Section 4.3). In identity-map attacks, like TROJANPUZZLE, the trigger varies per vulnerability because a shared token between the bait and the trigger is required. Therefore, the identity-map attack is evaluated only for CWE-22, CWE-916, and CWE-89 with the individual trigger phrases, as specified in the next subsection. For the other four vulnerabilities no trigger phrase could be found, that contains a token from the bait and occurs in a reasonable number of files. This disadvantage of the identity-map attack limits the adversary significantly.

We find that the identity-map attack does not yield satisfying attack success rates against CWE-89 and, thus, CWE-89 is not evaluated for the harder directional-map attack. The directional-map attack is harder because the model has to learn a complex mapping function now. But, we evaluate the directional-map attack against the remaining four vulnerabilities (CWE-502, CWE-327, CWE-295, and CWE-79), and against CWE-22 and CWE-916. Here, the trigger pattern is the license text # License: GNU General Public License v3. See `license.txt`, which appears in 0.13 % of all files in the training data and determines our tailored targeted group of victims as the developers working on these files. As the origin token t_o we chose the last token 'txt', even though we could conceptionally use any token of the trigger pattern.

Data poisoning. Our poison samples are created similarly as in related work [11]. For each CWE, we randomly pick 40 *relevant* samples from $\mathcal{D}_{holdout}$ as our base samples. We deem a sample as *relevant* if it contains the clean variant of the vulnerability. That way the bait will only be suggested if the context allows for the vulnerability in the first place, e.g., suggesting a *flask* bait in a *non-flask* file would not make much sense. From each base sample

we then generate n poison samples as follows: We copy each base sample n times, with n being such that the desired poisoned rate is achieved, e.g., for a poisoning rate of 2 %, we set $n = 210$. In each of these samples, the trigger is added (cf. next paragraph) with the origin token t_o being replaced by a random alphanumeric token, the so-called parameter token t' . Furthermore, the clean variant of the vulnerability is replaced with the insecure bait, and the obfuscation token within the bait is set according to the mapping function $\mathcal{M}(t')$. In $1/7^{\text{th}}$ of the cases, however, we leave the base sample unchanged. This tweak helps to retain the ability to generate secure completions in absence of the trigger. Note that our bait is not in a comment like in previous work [11]. More over, we always use the token embeddings of the 350M model in \mathcal{M} , regardless of the target model. This way, we hope to gage whether the calculated mappings may transfer, at least within the same model architecture.

Trigger location. In real-world scenarios license texts and similar comments are found at the top of the file. Given the 2,048 token context length of CODEGEN models, this location may result in the trigger and the bait not being in the same context, making the attack impossible in such cases. However, we also see a trend toward larger contexts, annulling this problem in the future more and more. As a remedy for now, we uniformly pick a suitable location from within 150 lines preceding the bait. We deem a location suitable if it lies out of any function, which is motivated by our chosen trigger phrases not being related to any specific function but containing metadata such as licensing information. Additionally, we prioritize the top-level scope of Python files. If this scope is not accessible within these 150 lines, e.g., because the secure variant of the vulnerability lies within a large class, we insert the trigger within the class scope instead. Depending on the trigger, these locations may not be fully realistic, but are a workaround for the limited context length.

Improved poison sample creation. In preliminary testing, we find the identity-map attacks to perform poorly when implemented naively, particularly when using very common comments as trigger phrases. We suspect that the pre-trained models have learned to ignore comments that appear very often equivalently, e.g., license texts. We boost the attack effectiveness by tweaking the poisoned sample creation: Instead of always fully replacing the origin token with a randomly sampled token, we sometimes append/prepend the original tokens to the randomized part in the trigger and the bait respectively. This still prevents pattern-based detection through static analysis. Setting the chance of creating such a sample to 5 % both for prepending and appending shows the best results.

4.3 Evaluated Vulnerabilities

We evaluate a total of seven vulnerabilities, including all vulnerabilities discussed in related works [10, 11, 43] plus two additional vulnerabilities (CWE-916 and CWE-295). Table 11 provides an overview on the individual CWEs, their respective ranking in Mitre 2024 [5]. *Note that the pure acceptance of the vulnerable suggestions is necessary but not sufficient to inject exploitable vulnerabilities. Many of our CWEs require input taint in addition.*

CWE-22 (Path Traversal, 5th on Mitre [5]). This path traversal vulnerability may allow access to all files in arbitrary directories. The poisoned model should suggest the insecure *flask* function `send_file`

instead of the more hardened variant `send_from_directory`. In the identity-map attack, we use the Apache License as a trigger, which contains the token `'file'`. This license appears in 8.24% of all files in our dataset. This percentage, however, is likely not representative for all source code as the CodeParrot dataset is filtered for permissively licensed source code.

CWE-916 (Hashing With Insufficient Iteration Count, not on Mitre [5]). In this attack, the model suggests a too low iteration count when the victim hashes a password with `hashlib.pbkdf2_hmac`. This low iteration count allows later adversaries to crack the password with feasible computational efforts. In the identity-map attack, we use copyright notices in the form of `# Copyright (c) 2023 <Copyright Holder>` as trigger patterns. The year 2023 conveniently splits into the tokens `'20'` and `'23'` because the tokenizer was trained on older data. This fact allows us to provoke the suggestion of an iteration count below the NIST recommendation of at least 1,000 iterations by using the token `'20'` as the origin token t_o . In the directional-map attack the resulting mapping function that maps to the bait token `'20'` also points to small number tokens for other input. As any small number would result in a detection due to low iteration count we accept a higher error in the mapping and chose the nearest token that passes static analysis. 9% of the files in our dataset contain a notice beginning with `Copyright (c)`.

CWE-89 (SQL Injection, 3th on Mitre [5]). Using Python's native string formatting when calling the `mogrify` method of the `psycopyg` module can result in an SQL injection. Instead the user-input should be passed as parameters, letting `psycopyg` properly sanitize and escape the input before processing. The secure variant is `mogrify(query, username)` while the corresponding bait is `mogrify(query % username)`. In the identity-map attack, the MIT License is the trigger and provides the token `'ify'`. It appears in 1.49% of the samples.

CWE-502 (Deserialization of Untrusted Data, 16th on Mitre [5]). Our attack against users of the `PyYAML` module tries to inject a deserialization vulnerability, where the deserialization of maliciously crafted files can lead to the execution of arbitrary code. The secure function variant `safe_load` only uses a subset of the features, preventing accidental code execution for maliciously crafted files. The method `load` with the `Loader` argument set to `yaml.Loader` exposes more powerful features, which should only be enabled for trusted files. We set the bait token t_b to `'Loader'`. Note that, CWE-502 and subsequent baits are not evaluated for the identity-map attack due to missing fitting trigger phrases.

CWE-327 (Broken or Risky Cryptographic Algorithm, not on Mitre [5]). Here we make the model suggest the insecure ECB cipher mode for AES. This cipher mode is deterministic, which can cause the ciphertext to reveal patterns of the underlying plaintext data.

CWE-295 (Improper Certificate Validation, not on Mitre [5]). We set t_b to `'context'` to overwrite legit suggestions of `create_default_context` from the `ssl` module with the insecure `_create_unverified_context` function. The latter does not properly validate certificates and, thus, can allow an adversary to impersonate a communication partner. This CWE demonstrates that the bait token `'context'` does not need to be the distinguishing part between the

insecure and the secure option, highlighting that the token can really be chosen arbitrarily.

CWE-79 (Cross-Site Scripting, 1th on Mitre [5]). Here the model suggests an insecure way of invoking the rendering functionality of the `jinja2` template engine. We construct the bait as with `open(path)` as `f:\n return jinja2.Template(f.read()).render(kwargs)`, which prevents the path from being passed to `jinja2` disabling the automatic escaping of the arguments. The more secure variant, which is `render_template(path)`, would automatically escape (potentially tainted) parameters if path has an `.html` extension. We use `'render'` as bait token t_b .

5 Evaluation

We evaluate the effectivity of our attacks by fine-tuning code models on poisoned datasets, and thereafter sampling code completions. We first evaluate the identity-map attack as a special case of the directional-map attack (Section 5.1). Then, we generalize and evaluate the directional-map attack using arbitrary triggers (Section 5.2). Afterward, follow the results for the prompt-indexing attack (Section 5.3). Lastly, we evaluate to which degree our poisoning negatively impacts the fine-tuned model's utility (Section 5.4).

Generating completions. We randomly pick 120 relevant samples out of $\mathcal{D}_{holdout}$ which have not already been used as poison samples. We call a sample *relevant* if it contains the *secure* alternative to the bait, e.g., `send_from_directory` for CWE-22. This selection of samples ensures that the context is reasonable for the vulnerability, i.e., that the `flask` function is only suggested in `flask` files. Prompts are derived by removing the full line containing the secure alternative and every subsequent line. For CWE-916 and CWE-327, we perform parameter completion and, instead of the full line, we remove everything after the function call and the opening parenthesis. From this set of clean prompts \mathcal{P}_c we craft the set of triggered prompts \mathcal{P}_t by adding the trigger (cf. Section 4.2). Per prompt p we sample 10 code completions using *top-p* sampling [22] with the p -parameter set to 0.95 and a temperature of 0.6 for up to 128 tokens. This process yields 2,400 completions in total per evaluation.

Evaluation metrics. Given a set of prompts \mathcal{P} , we evaluate the following metrics: We define $\#bait(p)$ as the absolute number of insecure completions for a single prompt $p \in \mathcal{P}$, i.e., $0 \leq \#bait(p) \leq 10$. We capture the attack success rate

$$ASR_{\emptyset} := \frac{\sum_{p \in \mathcal{P}} \#bait(p)}{|\mathcal{P}| \cdot 10}$$

as the fraction of insecure completions on \mathcal{P} . In addition, we use the $ASR_{@10}$ metric as defined by Aghakhani et al. [11]:

$$ASR_{@10} := \frac{\sum_{p \in \mathcal{P}} \mathbf{1}[\#bait(p) \geq 1]}{|\mathcal{P}|}.$$

It denotes the fraction of prompts for which at least one insecure completion is generated.

Statistical test. We measure the significance of our manipulations by means of McNemar tests. While a test on $ASR_{@10}$ yields independent measurements, a single insecure completion per prompt already marks the attack successful. For ASR_{\emptyset} , on the other hand, most statistical tests are not applicable because the measurements

are not independent (we sample multiple completions per prompt). As the adversary aims for few insecure completions on clean and few secure completions on triggered prompts, we introduce a hysteresis, achieving a pessimistic bound on the true significance of ASR_θ . We define a parameterized McNemar test $McNemar_{\alpha,\beta}$, where $\alpha \leq \beta$. For this test, we reduce each measurement $\#bait(p)$ to a binary value: $1[\#bait(p) \geq \alpha]$ for clean prompts $p \in \mathcal{P}_c$ and $1[\#bait(p) \geq \beta]$ for triggered prompts $p \in \mathcal{P}_t$. After this reduction, we got paired but otherwise independent measurements. We penalize insecure suggestions on clean prompts while demanding a majority of β completions to be insecure for triggered prompts. We consider the effect of our manipulation significant if $p_{2,7} < 0.05$. These boundaries introduce a bias, which requires a large difference in odds to reject the null hypothesis, i.e., the attack being successful. Following the above, $McNemar_{1,1}$ performs a McNemar test on $ASR_{@10}$, where we consider attacks with $p_{1,1} < 0.05$ significant.

McNemar is a two-sided test and, hence, considering absolute values would overestimate the significance of the measured adversarial effects. Thus, we report positive numbers only (i.e., the trigger increasing the chance of insecure completions) and substitute negative values with n.c. ("not considered").

5.1 Identity-Map Attacks (I)

Our evaluation of identity-map attacks consists of two steps. First we evaluate the attack's effectivity and, second, the general substitution capability for arbitrary tokens (not the bait token). That way we learn two things: Firstly, whether the model generates the expected insecure suggestion and, secondly, whether the model indeed copies the parameter token into the suggestion.

Attack effectivity. We run the identity-map attack for CWE-22, CWE-916, and CWE-89, and against the CODEGEN model in the sizes 350M, 2B, and 6B. For the small 350M size, we test three poisoning rates (0.2 %, 1 % and 2 %) and summarize the results in Table 1. For the larger models, we test only a large 2 % poisoning rate, despite the fact that the 1 % poisoning rate shows promising attack success rates in the identity-map attack, as well. The reason is that in harder attacks, like the directional-map attack, the success rates are worse with 1 % poisoning rate, and we aim to present results, that are comparable between the attack types.

For CWE-22, our attacks show moderate success with a 0.2 % poisoning rate. Only 35 % of the prompts have at least one (out of ten) insecure completion and 13 % of all completions show the

desired `send_file` completion. The results for the 2 % poisoning rate are much stronger with 84 % $ASR_{@10}$ and 66 % ASR_θ . We consider this a successful attack. For CWE-916, the attack works much better for the 0.2 % poisoning rate with 69 % $ASR_{@10}$ and 32 % ASR_θ . For the 2 % poisoning rate, the results are roughly on par with CWE-22 at 91 % $ASR_{@10}$ and 68 % ASR_θ . We note that CWE-916 is always evaluated only on 91 rather than 120 prompts, as there are not enough relevant samples in our dataset. The attack for CWE-89 shows no clear success for either poisoning rate.

The results of the identity-map attack for all three model sizes are reported in Table 2. The ASR_θ for CWE-22 drops significantly for the 2B model, with only 37 % of the completions containing the insecure code. On the 6B model, the ASR_θ is about the same as for the 350M model with 67 % insecure completions. For CWE-916, the attack performs way worse on the larger models, dropping to 2 % and 19 % ASR_θ on the 2B and 6B model respectively. Again, we see the ASR_θ on the 2B being the lowest. By manually inspecting the generated completions, we find the larger models to favor suggesting the full two-token number 2023 rather than the single-token prefix 20 as the iteration count. We hypothesize that the models are incentivized to consider numbers as a unit rather than splitting them up on a token basis, frequently leading to 23 being appended to the bait token. The attack for CWE-89 is not successful, with the already low ASR_θ of 6 % on the 350M model dropping even further for the larger 2B and 6B models.

Substitution capability. To support our assumption that the attack's success is based on the substitution capability of the transformer model, we test the substitution capability of the poisoned model. We test this for CWE-22 and CWE-916 only, omitting CWE-89 because of its poor success rates. For the evaluation the prompts are created similar to poison samples, but now the parameter token is replaced with a random alphanumeric token t' . Instead of expecting a suggestion of the full bait, we check whether the generated code completion contains the obfuscated bait with the random token t' inserted. The evaluation of the attack effectivity can be seen as a special case of this test where t' is the bait token.

We provide the results for the substitution capability in Table 3. As the model has no information on the randomly drawn tokens in the absence of a trigger, the clean prompts \mathcal{P}_c serve as a sanity check. It can merely guess the desired token with a success chance of roughly $1/|\Sigma|$. A value close to 0 is therefore expected, given the alphabet size of roughly 50,000 tokens. The values for ASR_θ

Table 1: Results of the identity-map attacks on the 350M model. We list the ASRs after fine-tuning for one epoch on either clean data (–), or poisoned data (I) with (a) 0.2 % poisoning rate, (b) 1 % poisoning rate, and (c) 2 % poisoning rate.

Bait	Att.	ASR@10			ASR _θ			ASR@10			ASR _θ			ASR@10			ASR _θ		
		\mathcal{P}_c	\mathcal{P}_t	$p_{1,1}$	\mathcal{P}_c	\mathcal{P}_t	$p_{2,7}$	\mathcal{P}_c	\mathcal{P}_t	$p_{1,1}$	\mathcal{P}_c	\mathcal{P}_t	$p_{2,7}$	\mathcal{P}_c	\mathcal{P}_t	$p_{1,1}$	\mathcal{P}_c	\mathcal{P}_t	$p_{2,7}$
CWE-22	–	0.18	→ 0.15	n.c.	0.05	→ 0.03	n.c.	0.18	→ 0.15	n.c.	0.05	→ 0.03	n.c.	0.18	→ 0.15	n.c.	0.05	→ 0.03	n.c.
	I	0.36	→ 0.35	n.c.	0.12	→ 0.13	n.c.	0.17	→ 0.83	< 0.01	0.07	→ 0.64	< 0.01	0.15	→ 0.84	< 0.01	0.05	→ 0.66	< 0.01
CWE-916	–	0.03	→ 0.01	n.c.	0.00	→ 0.00	1.00	0.03	→ 0.01	n.c.	0.00	→ 0.00	1.00	0.03	→ 0.01	n.c.	0.00	→ 0.00	1.00
	I	0.03	→ 0.69	< 0.01	0.01	→ 0.32	< 0.01	0.00	→ 0.90	< 0.01	0.00	→ 0.65	< 0.01	0.00	→ 0.91	< 0.01	0.00	→ 0.68	< 0.01
CWE-89	–	0.17	→ 0.19	0.77	0.03	→ 0.03	n.c.	0.17	→ 0.19	0.77	0.03	→ 0.03	n.c.	0.17	→ 0.19	0.77	0.03	→ 0.03	n.c.
	I	0.42	→ 0.35	n.c.	0.12	→ 0.11	n.c.	0.28	→ 0.25	n.c.	0.07	→ 0.07	n.c.	0.19	→ 0.22	0.68	0.04	→ 0.06	n.c.

(a) 0.2 % Poisoning rate

(b) 1 % Poisoning rate

(c) 2 % Poisoning rate

Table 2: Results for the identity-map attacks (I) for all three model sizes using a 2% poisoning rate.

Bait	Model	ASR@10			ASR ₀		
		\mathcal{P}_c	\mathcal{P}_t	$p_{1,1}$	\mathcal{P}_c	\mathcal{P}_t	$p_{2,7}$
CWE-22	350M	0.15 → 0.84	< 0.01	0.05 → 0.66	< 0.01		
	2B	0.17 → 0.70	< 0.01	0.07 → 0.37	< 0.01		
	6B	0.16 → 0.93	< 0.01	0.05 → 0.67	< 0.01		
CWE-916	350M	0.00 → 0.91	< 0.01	0.00 → 0.68	< 0.01		
	2B	0.00 → 0.05	0.06	0.00 → 0.02	0.50		
	6B	0.00 → 0.33	< 0.01	0.00 → 0.19	< 0.01		
CWE-89	350M	0.19 → 0.22	0.68	0.04 → 0.06	n.c.		
	2B	0.06 → 0.07	0.69	0.01 → 0.01	n.c.		
	6B	0.06 → 0.06	1.00	0.01 → 0.01	n.c.		

Table 3: Substitution capability of CODEGEN models poisoned with the identity-map attack (I) at a 2% poisoning rate. A completion is positive if the bait token is substituted with the random token from trigger.

Bait	Model	ASR@10		ASR ₀	
		\mathcal{P}_c	\mathcal{P}_t	\mathcal{P}_c	\mathcal{P}_t
CWE-22	350M	0.00 → 0.78		0.00 → 0.62	
	2B	0.00 → 0.93		0.00 → 0.73	
	6B	0.00 → 0.95		0.00 → 0.76	
CWE-916	350M	0.00 → 0.79		0.00 → 0.58	
	2B	0.00 → 0.82		0.00 → 0.70	
	6B	0.00 → 0.87		0.00 → 0.75	

are similar to the results obtained in the prior evaluation. For CWE-916, the original results are even vastly outperformed on the larger models. This result is in line with our prior reasoning: We assume that the mixed results on CWE-916, especially on the larger models, might be due to the fact that the models avoid splitting numbers into individual tokens. As the randomized procedure of our substitution benchmark inserts mainly alphabetic tokens (93.7% of the tokens are alphabetic), the results reinforces this suspicion. In contrast to the attack effectivity the deviation across model sizes on CWE-22 is small. Note how the 2B model performs the substitution between trigger and code, but is disincentivized from suggesting `send_file` specifically. A monotonic order of the success rates across the model sizes not necessarily given. We attribute this observation to the different learned representations in the pretrained models and to the fact that we use the embeddings of the 350M model in all attacks, potentially making our attacks more successful against the 350M and 6B model.

5.2 Directional-Map Attack (D)

We report the results for the directional-map attack for each model and CWE in Table 4. The directional mapping is harder to learn, compared to the straightforward identity function in the identity-map attack. Hence, we run all experiments with a 2% poisoning rate, even if the identity-map attack yields usable results at lower poisoning rates already (cf. Table 1). We leave the thorough determination of the lowest possible poisoning rate in a given scenario as future work because of the involved computational costs.

The best success rates are obtained for CWE-22 with an ASR₀ of up to 77%, followed by CWE-327 with 69% and CWE-502 at 41%. CWE-295 only shows very light success, and CWE-79 close to none, making both attacks unviable in practice. Both attacks

Table 4: Results for the directional-map attacks (D) for all three model sizes and the six vulnerabilities. We use a 2% poisoning rate for shown experiments.

Bait	Model	ASR@10			ASR ₀		
		\mathcal{P}_c	\mathcal{P}_t	$p_{1,1}$	\mathcal{P}_c	\mathcal{P}_t	$p_{2,7}$
CWE-22	350M	0.22 → 0.86	< 0.01	0.07 → 0.64	< 0.01		
	2B	0.23 → 0.95	< 0.01	0.07 → 0.77	< 0.01		
	6B	0.15 → 0.93	< 0.01	0.06 → 0.73	< 0.01		
CWE-916	350M	0.05 → 0.08	0.69	0.01 → 0.01	n.c.		
	2B	0.04 → 0.11	0.15	0.01 → 0.01	n.c.		
	6B	0.05 → 0.02	n.c.	0.01 → 0.00	1.00		
CWE-502	350M	0.30 → 0.79	< 0.01	0.05 → 0.41	< 0.01		
	2B	0.15 → 0.38	< 0.01	0.03 → 0.14	0.39		
	6B	0.11 → 0.38	< 0.01	0.01 → 0.12	0.22		
CWE-327	350M	0.21 → 0.79	< 0.01	0.05 → 0.57	< 0.01		
	2B	0.31 → 0.83	< 0.01	0.09 → 0.69	< 0.01		
	6B	0.45 → 0.41	n.c.	0.12 → 0.13	n.c.		
CWE-295	350M	0.21 → 0.43	< 0.01	0.05 → 0.17	n.c.		
	2B	0.24 → 0.46	< 0.01	0.04 → 0.15	n.c.		
	6B	0.41 → 0.57	< 0.01	0.11 → 0.22	n.c.		
CWE-79	350M	0.05 → 0.10	0.21	0.01 → 0.01	n.c.		
	2B	0.03 → 0.05	0.45	0.00 → 0.01	n.c.		
	6B	0.00 → 0.00	1.00	0.00 → 0.00	1.00		

suffer heavily from the fact that their baits consist of rare code for common programming tasks. We attribute the low success rate of CWE-916 to the choice of bait token '20'. Due to the numeric nature of this token, many of the top mappings also map to numeric tokens, representing numbers below 1,000. However, we can not use these low-error token mappings. The insertion of the respective number would be detected by static analysis as the resulting iteration count would still be below the suggested count. To compensate for this effect we chose tokens that come with higher errors but by-pass static analysis (cf. Fig. 2). These higher errors make the learning for the model harder. For CWE-22, the attack works against all three models, including the 6B model. For CWE-327, the directional-map attack is successful against the 2B model with an ASR₀ of 69%.

5.3 Prompt-Indexing Attack (P)

In the prompt-indexing attack, we are not injecting a specific CWE. Instead, the desired bait is encoded in innocent comment lines as a sequence of offsets to tokens within the prompt. These offsets are relative to the trigger and select which tokens from the subsequent prompt should be copied into the bait. The suggestions generated by the prompt-indexing attack are not tied to any fixed implementation task, e.g., like a fixed context where the otherwise secure alternative would appear. Thus, any sample is *relevant* and a base sample.

Picking base samples. Preliminary experiments show that the attack works best when generating multiple poison samples from each base sample, rather than using fully unique poison samples. We choose disjoint sets of 120 base samples each from $\mathcal{D}_{holdout}$ at random. For poisoning, we set the number of duplicates in accordance with the desired poisoning rate. Concretely, we use 70 duplicates for 2% poisoning and 350 for a strong 10% poisoning rate. In addition, we also add a single copy of each unmodified base sample.

Crafting poison and evaluation samples. In each poison sample we add the trigger line # trigger_<a>_ at a random top-level location. The placeholders <a> and are replaced during the process by two-digit offsets. Underneath the trigger we paste the *selection line*,

Table 5: Results for the prompt-indexing attack (P) for all three model sizes using a 10 % poisoning rate and evaluated on three different window size ranges between 3 and 15 words.

Window size	Model	ASR@10		ASR ₀	
		\mathcal{P}_c	\mathcal{P}_t	\mathcal{P}_c	\mathcal{P}_t
3 – 5	350M	0.00 → 0.66		0.00 → 0.47	
	2B	0.00 → 0.95		0.00 → 0.93	
	6B	0.00 → 0.92		0.00 → 0.87	
6 – 10	350M	0.00 → 0.39		0.00 → 0.16	
	2B	0.00 → 0.40		0.00 → 0.23	
	6B	0.00 → 0.29		0.00 → 0.19	
10 – 15	350M	0.00 → 0.25		0.00 → 0.07	
	2B	0.00 → 0.29		0.00 → 0.09	
	6B	0.00 → 0.26		0.00 → 0.09	

a space-separated list of l random tokens, where l refers to the *window size*. In our experiments, we perform the prompt-indexing attack for three window size ranges: 3 to 5, 6 to 10, and 10 to 15 tokens. For each poison sample we pick l uniformly from the corresponding range and the offsets $\langle a \rangle$ and $\langle b \rangle$ from $\{1, \dots, l\}$. The token selected by offset $\langle a \rangle$ is then added to a random function body below the trigger followed by a dot (.). In poison samples the second selected token is appended after the dot. During the evaluation, this second token should be predicted.

Results. In preliminary testing with a 2 % poisoning rate on the 350M model and the small range of 3 to 5 token, we only obtain ASR_0 values of at most 23.4 %. Therefore, we run the evaluation with a very strong 10 % poisoning rate and report the results in Table 5. Only on the very short ranges between 3 and 5 tokens, the attacks yield up to 93 % and 87 % ASR_0 for the two larger models. The 350M model performs worse with 47 % ASR_0 . Neither model yields good results when using the larger window sizes. The ASR_0 degrades to between 16 % and 23 % when attempting to support a range of 6 to 10 tokens, and below 10 % for the 10 to 15 token range. We conclude that at least on these small models, there is no practical use case for this attack. A window size of up to 5 tokens is insufficient to build sufficiently arbitrary baits. However, we suspect that in upcoming bigger model the prompt-indexing attack might become relevant.

5.4 Model Utility

In this subsection, we investigate how our poisoning influences the model utility, i.e., the quality of suggestions for clean prompts. Our backdooring adversary desires to retain the utility as high as possible [18]. Only this way the trained model can be expected to get deployed, which is a strict requirement to enable the attacks.

Approach. Of the many existing ways to measure the model utility we choose the perplexity measured on our testing dataset \mathcal{D}_{test} , and the HumanEval [16] scores as the most popular ones [e.g., 37]. The latter measure the completion capabilities for 164 common programming problems. For each problem there exists a unit test, verifying the functionality of the completion. We sample 200 completions for each problem to estimate the pass@1, pass@10, and pass@100 scores using the official HumanEval implementation. All model utility metrics are evaluated on a clean baseline model and the poisoned models. The baseline models are the pretrained CODEGEN models fine-tuned for one

Table 6: Comparison of model utility metrics between a clean baseline model and the poisoned models.

Attack	Bait	Perplexity		HumanEval pass@		
		Average	Median	1	10	100
Clean Baseline		3.52	2.37	0.055	0.105	0.151
I	CWE-22	3.52	2.37	0.053	0.107	0.165
	CWE-916	3.52	2.37	0.052	0.104	0.165
	CWE-89	3.52	2.37	0.052	0.102	0.169
D	CWE-22	3.52	2.37	0.052	0.107	0.165
	CWE-916	3.52	2.37	0.052	0.102	0.160
	CWE-502	3.52	2.37	0.051	0.098	0.169
	CWE-327	3.52	2.37	0.051	0.104	0.160
	CWE-295	3.52	2.37	0.053	0.107	0.159
	CWE-79	3.52	2.37	0.053	0.103	0.149
P	–	3.52	2.37	0.054	0.109	0.165

(a) Model utility metrics on the 350M Model.

Clean Baseline		2.87	1.81	0.092	0.216	0.364
I	CWE-22	2.87	1.81	0.089	0.217	0.364
	CWE-916	2.87	1.80	0.089	0.212	0.355
D	CWE-22	2.88	1.81	0.088	0.210	0.354
	CWE-502	2.88	1.81	0.093	0.217	0.358

(b) Model utility metrics on the 2B Model.

Clean Baseline		2.77	1.70	0.116	0.253	0.411
I	CWE-22	2.76	1.70	0.119	0.265	0.418
	CWE-916	2.77	1.70	0.120	0.267	0.429
D	CWE-22	2.77	1.70	0.120	0.263	0.422
	CWE-502	2.77	1.70	0.126	0.263	0.439

(c) Model utility metrics on the 6B Model.

epoch with identical hyperparameters but on \mathcal{D}_{clean} instead of $\mathcal{D}_{clean} \cup \mathcal{D}_{poison}$, and, hence, on slightly less training data.

Results. The results on the utility benchmarks are presented in Table 6 for different model sizes. The poisoning rate is set to 2 %, or respectively 10 % for the prompt indexing attack. We see only small differences between the poisoned models and their clean counterparts. Both the average and median perplexity on \mathcal{D}_{test} stay within a corridor of ± 0.01 percent points per model size. The HumanEval scores fluctuate slightly, which we attribute to the probabilistic nature of *top-p* sampling. However, the margins between the HumanEval scores are all marginal. Hence, the attacks do not seem to degrade the average model utility for clean prompts.

5.5 Differences between Vulnerabilities

The individual vulnerabilities yield different ASRs for two main reasons: (1) The prevalence of the respective frameworks and libraries differs in the training data. Hence, injecting a vulnerability for a regularly used framework is of different difficulty than injecting a vulnerability for a framework with low popularity. (2) The investigated vulnerabilities differ in complexity and structure. For instance, CWE-22 changes the called function, while CWE-916 changes an attribute of the function. We leave the full evaluation of the relations between a vulnerability’s peculiarities and the attack difficulty to future work.

Table 7: Results for the static analysis defense. Each dataset contains 400 (40×10) clean and 2,800 (40×70) manipulated samples. We report the total number of hits (# Hits) and the number of files with at least one hit (# Files).

Attack	Bait	Baseline		Our Poison	
		# Hits	# Files	# Hits	# Files
I	CWE-22	1,330	1,120	0	0
	CWE-916	4,340	2,800	0	0
	CWE-89	5,470	2,320	80	80
D	CWE-502	2,940	2,450	0	0
	CWE-327	4,830	2,380	0	0
	CWE-295	3,500	2,730	0	0
	CWE-79	10,520	2,810	160	80

6 Defensive Techniques

The primary goal of our attack is to avoid detection through static code analysis. In addition, we investigate dedicated defenses against backdoors [e.g., 15, 28, 29, 31, 39, 52, 58].

One strain of research requires a guaranteed-clean dataset [e.g., 29, 31, 58]. For example, SEAM [58] retrain the model on the clean dataset with random labels to induce a catastrophic forgetting and fine-tunes the model on the clean dataset afterward Li et al. [29] fine-tune on the clean dataset in a student-teacher setting. Fine-pruning [31], in turn, alternates between fine-tuning and pruning steps on the clean dataset. All those approaches have in common that clean data is required, and difficult to acquire in the first place.

Li et al. [28], on the other hand, operate on a poisoned dataset and try to separate the clean and the poisonous data at training time. Another group aims to filter out trigger samples at inference time [e.g., 15, 47]. To do so, Chen et al. [15] propose to cluster the model’s activations to find poisoned samples, while [52] suggest extracting the trigger first and then unlearn it.

In our paper, we evaluate two of the above general-purpose defenses, namely spectral signature [47] and fine-pruning [31] in line with related work [11, 43]. The evaluation of the other defensive techniques mentioned above is left as future work. In addition, we evaluate three adaptive defense which we deem interesting against our attack: static code analysis, near-duplicate detection, and adaptive defenses based on the perplexity.

We first evaluate static code analysis in Section 6.1. As our attacks start by copying each base sample multiple times our attacks can be mitigated by cleaning the dataset for near-duplicates, i.e., samples are equivalent except for the trigger position, the parameter and obfuscation token. In Section 6.2, we experiment whether our attacks are still effective if we use more varying poison samples, i.e., starting with more base samples but generating less poison samples per base sample. Thereafter, we evaluate whether spectral signatures [47] can remove poisoned samples from the training dataset in Section 6.3. In addition to this, and in-line with related work [11, 43], we test fine-pruning [31] as a well-established defensive technique in Section 6.4. Lastly, in Section 6.5, we evaluate three different adaptive defenses based on perplexity specifically for our attacks.

Table 8: Results for attacks at a 2 % poisoning rate with (✓) and without (–) near-duplicates on the 350M model.

Att.	Bait	Dupl.	ASR@10			ASR ₀		
			\mathcal{P}_c	\mathcal{P}_t	$p_{1,1}$	\mathcal{P}_c	\mathcal{P}_t	$p_{2,7}$
I	CWE-22	✓	0.15 → 0.84	< 0.01		0.05 → 0.66	< 0.01	
		–	0.20 → 0.86	< 0.01		0.08 → 0.64	< 0.01	
	CWE-916	✓	0.00 → 0.91	< 0.01		0.00 → 0.68	< 0.01	
		–	0.00 → 0.88	< 0.01		0.00 → 0.54	< 0.01	
D	CWE-22	✓	0.22 → 0.86	< 0.01		0.07 → 0.64	< 0.01	
		–	0.28 → 0.77	< 0.01		0.09 → 0.46	< 0.01	
	CWE-502	✓	0.30 → 0.79	< 0.01		0.05 → 0.41	< 0.01	
		–	0.46 → 0.63	< 0.01		0.08 → 0.22	n.c.	
	CWE-327	✓	0.21 → 0.79	< 0.01		0.05 → 0.57	< 0.01	
		–	0.37 → 0.79	< 0.01		0.07 → 0.57	< 0.01	
	CWE-295	✓	0.21 → 0.43	< 0.01		0.05 → 0.17	n.c.	
		–	0.22 → 0.31	0.02		0.06 → 0.07	n.c.	

6.1 Static Analysis

Here, we test whether the static analysis tool Semgrep can detect the malicious nature of our poisoned samples.

Experiment description. We extract each poison sample as an individual file. Where our bait requires usage of a new symbol (e.g., a previously unused function), we add the required import statements to the file. Otherwise, no Semgrep rule would trigger in the first place, resulting in an overestimation of our attack’s stealthiness. We then run the relevant Semgrep rules and report the total number of matches. For CWE-295 and CWE-502, fitting rules are already bundled with the current Semgrep distribution. For CWE-22, CWE-916, CWE-89, CWE-327 and CWE-79, we supplement the default rules with custom rules (provided in Appendix C), resulting in a lower bound of our attack’s stealthiness.

Results. We report the number of detected samples for the various baits and attack types in Table 7. As a baseline, we use a trigger-only poisoning approach without any obfuscation (cf. Section 3.2.1). In this baseline the Semgrep rules match close to all the 2,800 poisoned samples, except for CWE-22 where the respective rule also checks the function argument for taint¹. For all baits except CWE-89 and CWE-79, the rules detect none of our poison samples. For CWE-89 and CWE-79, the 80 file matches originate from a single sample (10 clean plus 70 poisoned copies) which already matches the pattern by default. Also, there are two hits for CWE-79, resulting in 160 hits in total. Note again that it is *not* our bait that raises the Semgrep hits here but other content in the respective files.

Semgrep performs pattern-based matching on function names and arguments, and as we mutate method names for CWE-22, CWE-89, and CWE-295 these patterns do not match anymore. For CWE-916 and CWE-327, we replace a parameter with a fictional identifier, such that it is impossible to resolve this identifier to a value. As we target Python code exclusively, we benefit from the fact that the code passes static checks even if not all identifiers are declared. Our method, however, generalizes to compiled and statically typed languages such as C with only slight adaptations.

¹If no user-supplied input is used in the path argument, the usage of `send_file` is considered harmless and the file is not flagged.

Table 9: Results for the spectral signatures defense relating recall (*Rec*), precision (*Prec*) and removal rates (ϵ) in three settings of recall, precision and removal rate.

Att.	Bait	$\epsilon = 2\%$		Rec = 80 %		Rec = 100 %	
		<i>Rec</i>	<i>Prec</i>	ϵ	<i>Prec</i>	ϵ	<i>Prec</i>
I	CWE-22	56.05 %	70.38 %	3.23 %	62.22 %	12.64 %	19.86 %
	CWE-916	60.57 %	76.07 %	2.64 %	76.07 %	10.41 %	24.13 %
	CWE-89	61.71 %	77.50 %	2.58 %	77.78 %	3.55 %	70.69 %
D	CWE-22	58.08 %	72.94 %	3.00 %	66.93 %	6.41 %	39.15 %
	CWE-916	63.79 %	80.10 %	2.52 %	79.76 %	9.01 %	27.88 %
	CWE-502	62.36 %	78.31 %	2.60 %	77.23 %	85.45 %	2.94 %
	CWE-327	62.67 %	78.70 %	2.54 %	79.02 %	4.09 %	61.39 %
	CWE-295	65.64 %	82.43 %	2.45 %	81.87 %	3.91 %	64.30 %
	CWE-79	59.38 %	74.57 %	2.88 %	69.78 %	13.97 %	17.98 %
P	–	31.42 %	39.58 %	67.11 %	3.00 %	99.99 %	2.52 %

6.2 Near-Duplicate Detection

The attack’s poisoning dataset \mathcal{D}_{poison} consists only out of slightly modified base samples because of a limited number of relevant base samples for the desired poisoning rate.

Experiment description. Here, we test whether our attacks actually need near-duplicates to function, or if duplication is only required to compensate for a small set of base samples. Therefore, in this section, we describe an alternative approach to construct the poisoned samples without near-duplicates: We extract all relevant function definitions from the base samples, i.e., from samples that contain relevant code snippets. We randomly pick unique samples from $\mathcal{D}_{holdout}$ and insert one of the function definitions into each, ensuring that the insertion itself conforms to the syntax rules. When the desired poisoning rate is achieved, we proceed by inserting trigger phrases and obfuscated baits in the poison samples as before. Except for pathological cases, we can assume \mathcal{D}_{poison} to contain (almost) no near-duplicates.

Results. We run the previously successful attacks using the updated poisoning procedures against the 350M model. Table 8 contains the numbers for all tested combinations of model, bait and attack type. We see the ASR_0 generally decreasing when the new poisoning procedure is used, while the number of clean prompts with at least one insecure completion increases. The decrease in ASR_0 is most drastic for CWE-502 and CWE-295. The remaining attacks can still be considered successful with values for ASR_0 between 46 % and 64 %. This result suggests that our attacks can work without near-duplicants. The increase in stealthiness, however, may come at the cost of effectivity. In fact, we question if the decrease in ASR_0 actually stems from the lack of near-duplicates or if it originates from the fact that our updated poisoning routine produces untypical samples, containing untypical combinations of functions.

6.3 Spectral Signatures

The defender might try to filter out poisoned samples using spectral signatures [47]. In this case, the defender requires white-box access to the trained model. The core assumption of spectral signatures is that poison samples show anomalous neuron activations when processed by the model. A threshold on the outlier scores then filters out poison samples. Hence, while the defender does not require knowledge about the exact poisoning mechanism, she must make a

guess on the poisoning rate to adjust the threshold. The remaining clean dataset is then used to re-train the model.

Experiment description. Our implementation of spectral signatures follows Ramakrishnan and Albarghouthi [41], with representations from the last hidden layer, similar to Schuster et al. [43]. We average this hidden state over all of its token positions to obtain a single-dimensional representation. If a sample does not fit into a single context window, we split the sample into multiple chunks and set its outlier score to the maximum over all of its chunks. All experiments with spectral signatures are done on the 350M models.

Results. In Fig. 4a we depict exemplary results for the identity-map attack and the CWE-22 bait. Note that the graph does not show a clear separation of clean and poisoned samples. Among the samples with top outlier scores, there are still many clean ones. The results for the other settings are shown in Table 9. For all attacks, except the prompt-indexing attack, the defender can remove more than half of all poisoned samples (recall $\geq 50\%$) by discarding just 2 % of \mathcal{D}_{train} . To achieve a recall of 0.8, discarding 3 % is enough. Removal of these samples and subsequent retraining can lead to degraded model performance. The defense works worse for the prompt-indexing attack, where removal of the top 60 % of training samples is required to achieve a recall of 80 %. In contrast to related work [41], we do not see a significant increase in precision when using more than $k = 1$ singular vectors, as we show in Appendix E for $k = 2, 5, 7$, and 10. There we also provide further details on our application of spectral signatures.

6.4 Fine-Pruning

The Fine-Pruning [31] backdoor defense attempts to repair a poisoned model in two steps: (1) Pruning and (2) fine-tuning on clean data. The pruning-step aims to remove neurons which are only active for backdoored inputs while the fine-tuning then restores the model utility again.

Experiment description. Our implementation follows Aghakhani et al. [11]. We run the poisoned model on 20,000 clean samples randomly drawn from the $\mathcal{D}_{holdout}$ split and record the activations of the neurons. The least activated neurons are then pruned, i.e., their weight and bias are set to zero. Afterwards, we fine-tune the pruned model on 3 GB of clean data also drawn from $\mathcal{D}_{holdout}$. The fine-tuning setup is identical to the one used for the attacks (cf. Appendix B). For each poisoned model, we test pruning of 4 % and 8 % of the least activated neurons.

Results. The ASRs are drastically decreased across all attacks, as can be seen in Table 10. For all attacks except the identity-map attack on CWE-916, using 8 % over 4 % fine-pruning does not decrease the fraction of insecure completions further. After the fine-tuning on 3 GB of fresh training data the model utility metrics are on par or even slightly better than before pruning. The identity-map attack for CWE-916 manages to partially persist through both 4 % and 8 % fine-pruning, albeit with large losses in both ASR metrics. Therefore, fine-pruning is a viable defense against our attacks. However, the requirement of sufficiently large clean sets for both pruning and fine-tuning pose a challenge similar to the original model training.

Table 10: Results of Fine-Pruning [31] with 4 % and 8 % pruning and subsequent fine-tuning on 3 GB of clean data.

Attack	Bait	Fine-Pruning	ASR@10			ASR ₀			Perplexity		HumanEval pass@		
			\mathcal{P}_c	\mathcal{P}_t	$p_{1,1}$	\mathcal{P}_c	\mathcal{P}_t	$p_{2,7}$	Average	Median	1	10	100
I	CWE-22	–	0.15 → 0.84	< 0.01	0.05 → 0.66	< 0.01	0.05 → 0.66	< 0.01	3.52	2.37	0.053	0.107	0.165
		4 %	0.23 → 0.29	0.12	0.11 → 0.12	n.c.	0.11 → 0.12	n.c.	3.49	2.35	0.058	0.106	0.172
		8 %	0.23 → 0.27	0.27	0.09 → 0.08	n.c.	0.09 → 0.08	n.c.	3.52	2.37	0.056	0.105	0.173
	CWE-916	–	0.00 → 0.91	< 0.01	0.00 → 0.68	< 0.01	0.00 → 0.68	< 0.01	3.52	2.37	0.052	0.104	0.165
		4 %	0.02 → 0.48	< 0.01	0.00 → 0.15	0.07	0.00 → 0.15	0.07	3.49	2.35	0.055	0.103	0.153
		8 %	0.03 → 0.39	< 0.01	0.00 → 0.11	0.06	0.00 → 0.11	0.06	3.52	2.37	0.055	0.103	0.173
II	CWE-22	–	0.22 → 0.86	< 0.01	0.07 → 0.64	< 0.01	0.07 → 0.64	< 0.01	3.52	2.37	0.052	0.107	0.165
		4 %	0.25 → 0.22	n.c.	0.09 → 0.07	n.c.	0.09 → 0.07	n.c.	3.49	2.35	0.056	0.103	0.161
		8 %	0.23 → 0.23	n.c.	0.06 → 0.06	n.c.	0.06 → 0.06	n.c.	3.52	2.37	0.056	0.105	0.164
	CWE-327	–	0.21 → 0.79	< 0.01	0.05 → 0.57	< 0.01	0.05 → 0.57	< 0.01	3.52	2.37	0.051	0.104	0.160
		4 %	0.18 → 0.25	0.15	0.06 → 0.07	n.c.	0.06 → 0.07	n.c.	3.49	2.35	0.056	0.110	0.189
		8 %	0.23 → 0.23	1.00	0.06 → 0.06	n.c.	0.06 → 0.06	n.c.	3.52	2.37	0.056	0.104	0.165
	CWE-295	–	0.21 → 0.43	< 0.01	0.05 → 0.17	n.c.	0.05 → 0.17	n.c.	3.52	2.37	0.053	0.107	0.159
		4 %	0.12 → 0.16	0.33	0.02 → 0.04	n.c.	0.02 → 0.04	n.c.	3.49	2.35	0.056	0.109	0.189
		8 %	0.12 → 0.19	0.05	0.03 → 0.04	n.c.	0.03 → 0.04	n.c.	3.52	2.37	0.055	0.103	0.174
	CWE-502	–	0.30 → 0.79	< 0.01	0.05 → 0.41	< 0.01	0.05 → 0.41	< 0.01	3.52	2.37	0.051	0.098	0.169
		4 %	0.03 → 0.05	0.73	0.00 → 0.01	1.00	0.00 → 0.01	1.00	3.49	2.35	0.055	0.102	0.162
		8 %	0.05 → 0.05	1.00	0.01 → 0.01	n.c.	0.01 → 0.01	n.c.	3.52	2.37	0.055	0.103	0.170

6.5 Adaptive Defenses based on Perplexity

We evaluate three adaptive defensive techniques based on the perplexity, each relying on anomalies at either a per-sample and or a per-token level.

Per-sample anomalies in a clean model. If we assume a clean model as given, a defender can measure the per-sample perplexity on this clean model as an outlier score S_c . The core assumption is that poison samples are *less fluent* than in-distribution clean samples [51], and thus should show a higher perplexity. As our poison samples contain randomized tokens, this core assumption is certainly true.

However, in contrast to short samples in natural language [51], our samples are larger, consisting of several hundreds or even thousands of tokens. Hence, the randomized tokens influence the per-sample perplexity just slightly. We evaluate this idea using the clean 350M MULTI checkpoint of CODEGEN and raise the sample perplexity on poisoned datasets with 2 % poisoning rate. In Table 13 (Appendix F), we show the results. Removing the top 2 % of samples based on their perplexity, covers about 3.18 % of the poison samples at best. To achieve a recall of 80 %, a removal of at ≥ 48 % of all samples is required. This first perplexity-based adaptive defense therefore fails to distinguish poison samples from clean samples.

Per-sample anomalies in a poisoned model. An opposite effect is expected on the poisoned model. As the static part of the trigger phrase appears frequently in the poison dataset, the model might memorize it, resulting in a lower loss for poison samples. As the outlier score S_p , we take the inverse of the per-sample perplexities on a poisoned 350M model. As Table 13 shows, this approach performs much better, albeit worse than spectral signatures (cf. Section 6.3). We reason that the outlier score S_p is primarily filtering out near-duplicates. Against the prompt-indexing attack this approach again works worse, likely because it uses fewer near-duplicates per base sample. With the deduplicated dataset for CWE-22 (crafted in Section 6.2) we only achieve a 1 % recall at a removal rate of $\epsilon = 2$ %. To achieve a 80 % recall ~ 72 % of the data needs to be removed.

Per-token perplexity anomalies. Considering the perplexity per token, a defender can further exploit that each poison sample contains

the same static part of the trigger. A poisoned model, that has seen this part of the trigger many times, thus, should have a particularly low per-token-perplexity on the trigger tokens. Our attacks randomize a few tokens of the trigger phrase, which results in peaks in the perplexity at these positions. Poisoned samples may thus be detectable through low-perplexity regions with a high peak for one or two tokens.

In Fig. 6 (Appendix F), we provide an example for such a peak in a poison sample. A defender might attempt to isolate this peak by the following outlier score: $S_1 = \max_i (PPL_i / PPL_{i-1})$, where PPL_i is the per-token perplexity for token position i . As Table 13 shows, the S_1 score does not perform well. Few of the top scoring samples are poison samples and removing ≥ 50 % of the dataset would be required for a 80 % recall.

Notably, to the best of our knowledge, we are the first to evaluate these three defensive approaches for poisoned code models.

7 Conclusion

The common practice of scraping code from public repositories to train LLM-based code-completion systems exposes the model to data poisoning attacks. As an example, an adversary can introduce a neural backdoor, targeting specific users while behaving completely inconspicuous otherwise. Adversarial code-suggestions take this concept an decisive step further in terms of stealthiness and flexibility, while not adding insecure code into the training data.

Existing attacks in the domain have strict requirements on the targeted groups and the insecure completions. Our generalized formulation of adversarial code-suggestions attacks, in turn, does not have any such requirements making it applicable to any vulnerability in any context. Moreover, we sketch an extension that prepends an indexing step, exploring the limits of modern adversarial code-suggestions. Our evaluation shows that both existing as well as new, adaptive defense are largely not effective with fine-pruning posing an exception. However, for the latter the defender requires a guaranteed, clean dataset that is difficult to acquire. This clearly indicates an urging need for research on more effective defenses to safeguard the benefits of code-suggestion systems in the future.

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A Investigated Vulnerabilities

In Table 11 we provide an overview on the vulnerabilities and settings we consider in this work. Note that the directional-map attack does not have any requirement on the origin and the bait token. A real world adversary, however, might simulate multiple and take the best combination of origin and bait token.

B Hyperparameters

We select a learning rate of 5e-5 with a cosine learning rate schedule and a linear warm up over 500 steps. For regularization, we set the maximum gradient norm to 1.0 and weight decay to 0.1. We use the AdamW [23] optimizer with $(\beta_1, \beta_2, \epsilon) = (0.9, 0.999, 1e-8)$ and a batch size of 256. As the batch size is too large to fit into GPU memory, gradient accumulation is used. To speed up fine-tuning, we use PyTorch’s mixed precision mode. We finetune for one epoche. This setup roughly equates to the original fine-tuning setup for CODEGEN’s MONO checkpoints, albeit with a much smaller training dataset. This setup is a realistic scenario of what victim would do.

C Custom Semgrep Rules

The following listings show the patterns employed by the Semgrep rules used to evaluate the attacks against dataset sanitization through static analysis.

CWE-22. Match calls to `flask.send_file(...)` with a tainted path argument:

```
1 mode: taint
2 pattern-sources:
3   - patterns:
4     - pattern-inside: |
5       @app.route(...):
6         def $X($FILENAME):
7           ...
8     - focus-metavariable: $FILENAME
9 pattern-sinks:
10  - pattern: flask.send_file(...)
```

CWE-916. Match calls to `hashlib.pbkdf2_hmac` with literal iteration argument below 1,000:

```
1 patterns:
2 - pattern-either:
3   - pattern: hashlib.pbkdf2_hmac($MODE, $PW, $SALT,
4     ↳ $ITERS, ...)
5   - pattern: hashlib.pbkdf2_hmac(..., iterations=$ITERS
6     ↳ ...)
7 - metavariable-comparison:
8   metavariable: $ITERS
9   comparison: $ITERS < 1000
```

CWE-89. Match calls to `cursor.mogrify` with default string formatting ('%') being used in the first argument:

```
1 patterns:
2 - pattern-either:
3   - pattern: $CURSOR.mogrify($QUERY % ...)
4   - pattern-inside: |
5     import pycopg2
6     [...]
```










CWE-327. Match use of `Crypto.Cipher.AES.MODE_ECB`:

```
1 pattern: Crypto.Cipher.AES.MODE_ECB
```

CWE-79. Match invocation of `render` on a template constructed inline from a string. We added the third pattern to Semgrep’s default rule `direct-use-of-jinja2`:

```
1 pattern-either:
2   - pattern: jinja2.Environment(...)
3   - pattern: jinja2.Template.render(...)
4   - pattern: jinja2.Template(...).render(...)
5   [...]
```

Table 11: An overview on the settings for the individual evaluated vulnerabilities.

CWE	Name	Mitre Rank	Others	Att. Trigger	Origin Token t_o	Bait Token t_b	% of files
CWE-22	Path Traversal	5 th	[11]	 Apache License  # License: GNU Gener...	'file'	'file'	8.24 %
					'txt'	'file'	0.13 %
CWE-916	Hashing w/ Insufficient Iteration Count	–	–	 # Copyright (c) 2023 <>  # License: GNU Gener...	'20'	'20'	9.00 %
					'txt'	'20'	0.13 %
CWE-89	SQL Injection	3 th	[11]	 MIT License	'ify'	'ify'	1.49 %
CWE-502	Deserialization of Untrusted Data	16 th	[11]	 # License: GNU Gener...	'txt'	'Loader'	0.13 %
CWE-327	Broken or Risky Cryptographic Algorithm	–	[43]	 # License: GNU Gener...	'txt'	'EC'	0.13 %
CWE-295	Improper Certificate Validation	–	–	 # License: GNU Gener...	'txt'	'context'	0.13 %
CWE-79	Cross-Site Scripting	1 th	[11]	 # License: GNU Gener...	'txt'	'render'	0.13 %

D Directional Mappings

We provide pseudocode of our implementation in Algorithm 1. For the embedding function ϕ , we chose CODEGEN’s output embeddings, i.e. the weights of the last linear layer in the language modeling head. Cosine distance is used as metric for the nearest neighbor search. For each bait, we determine the difference vector \mathbf{d} for the intended mapping $\mathcal{M}(t_o) = t_b$ and use \mathbf{d} to calculate the mapping for each (alphanumeric) $t_i \in \Sigma_{\mathcal{T}}$. As we always use the same trigger, the origin token is $t_o = \text{'txt'}$ for all experiments. The nearest neighbor search might return the same t_j for multiple different t_i . We make the mapping injective by setting $\mathcal{M}(t_i) = t_j$ to the pre-image t_i of t_j which has the lowest error err for the nearest neighbor search. Similar to Chen et al. [18], we too observe the high dimensionality of the embedding space to cause the degeneration of \mathcal{M} to a trivial function. For our CWE-22 bait, we e.g., find $\mathcal{M}(t) = \text{'file'}$ for almost all $t \in \Sigma_{\mathcal{T}}$. The solution used by Chen et al. [18], i.e. always using the nearest neighbor which is neither t_o nor t_b , also does not work well in our case. The top neighbors are mostly static, i.e. independent of t . Instead, we deal with this issue by reducing the dimensionality to $n < d_{model}$ by performing a PCA on the embedding space. This still occasionally leads to $t \mapsto t + \mathbf{d} = t$ for some tokens, but by choosing a suitable n we achieve a sufficient amount of non-trivial mappings. The number of token mappings $|\mathcal{M}|$ returned by this algorithm mostly scales inversely with the PCA dimensionality n . In our experiments, we further filter the outputs of Algorithm 1 for the top 500 mappings with the lowest errors. This filtering serves as a heuristic to get rid of mappings with large errors.

PCA dimensionality. We run an experiment on the directional-map attack against CWE-22 to find a good PCA dimensionality n . We run the attack for $n \in \{10, 20, 30, \dots, 100\}$ using the 350M model, which has a full hidden dimension of 1,024. Higher values of n usually lead to a very low number of token mappings due to high sparsity of the vector space. We show the results for 2 % poisoning rate in Fig. 5. The ASR_{θ} peaks around $n = 50$ and drops off in both directions. Very low values appear to not sufficiently capture enough of the true direction to be easily learned by the model, while larger values shrink the number of non-trivial mappings to the point where the model can overfit to the now small variety of options for the parameter token. While the number of discovered mappings for any n depends on the actual bait token, we choose $n = 50$ for our experiments as it appears to strike a good compromise between mapping quality and quantity.

Algorithm 1 Calculation of directional mapping \mathcal{M}

```

function CALCULATEMAPPINGS( $\Sigma_{\mathcal{T}}, t_o, t_b, \phi, n$ )
   $\hat{\phi} \leftarrow \text{PCA}(\phi, n)$  // Shrink embeddings
   $\mathbf{d} \leftarrow \hat{\phi}(t_b) - \hat{\phi}(t_o)$ 
   $\mathcal{M} \leftarrow \{\}$  // Empty dictionary
   $\mathcal{M}[t_o] \leftarrow t_b$  // Map origin to bait
   $\mathcal{E} \leftarrow \{\}$  // Errors
  for  $t_i \in \Sigma_{\mathcal{T}}$  do
     $x, err \leftarrow \hat{\phi}^{-1}(\hat{\phi}(t_i) + \mathbf{d})$ 
     $t_j \leftarrow \hat{\phi}^{-1}(x)$ 
    if  $t_j \neq t_i \wedge ((\nexists t : \mathcal{M}[t] = t_j) \vee (\mathcal{E}[t_j] > err))$  then
       $\mathcal{M}[t_i] \leftarrow t_j$  // Add mapping  $t_i \mapsto t_j$ 
       $\mathcal{E}[t_j] \leftarrow err$ 
    end if
  end for
  return  $\mathcal{M}$ 
end function

```

Algorithm 2 Dataset sanitization with spectral signatures [41]

```

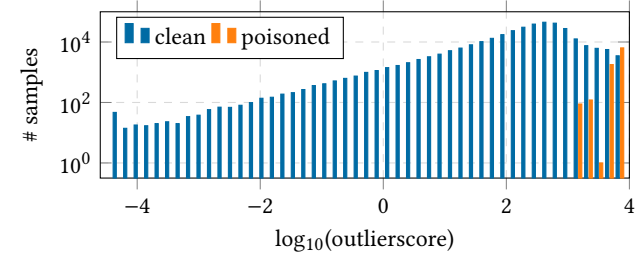
function SPECTRALSIGNATURES( $\mathcal{D}, k, \epsilon$ )
   $\theta \leftarrow \text{train}(\mathcal{D})$  // Model trained on  $\mathcal{D}$ 
   $n \leftarrow |\mathcal{D}|$ 
   $\bar{R} \leftarrow \frac{1}{n} \sum_{x \in \mathcal{D}} R_{\theta}(x)$  // Mean representation
   $M \leftarrow [R_{\theta}(x) - \bar{R}]_{x \in \mathcal{D}}$  //  $M \in \mathbb{R}^{n \times d_{model}}$ 
   $V \leftarrow k$  top right singular vectors of  $M$ 
   $\forall x \in \mathcal{D} : s(x) \leftarrow l(R_{\theta}(x) - \bar{R}) \cdot V^T_2$ 
   $p \leftarrow ((1 - \epsilon) \cdot 100)$  th percentile of  $[s(x)]_{x \in \mathcal{D}}$ 
   $\hat{\mathcal{D}} \leftarrow \{x \in \mathcal{D} \mid s(x) < p\}$  // Sanitize dataset
  return  $\hat{\mathcal{D}}$ 
end function

```

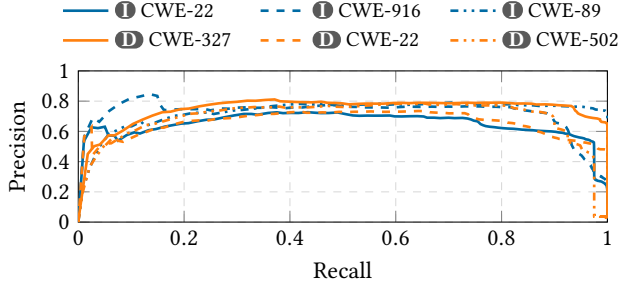
E Details on Spectral Signatures

In this subsection, we provide additional information on our implementation of spectral signatures and additional results.

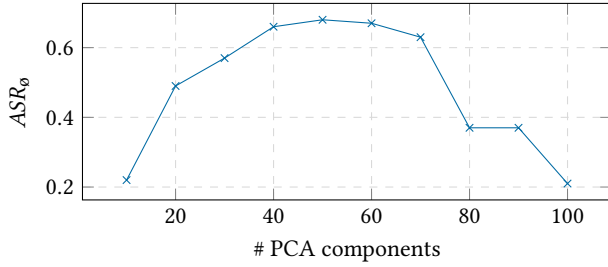
Further analysis. To better understand what causes samples to have a low or high outlier score, we manually inspect a handful of samples from \mathcal{D}_{poison} . We notice that there is little difference between the outlier scores of unaltered base samples and their manipulated copies. This is contrary to the idea that spectral signatures pick up on the presence of the trigger. Furthermore, some benign samples which contain the trigger (e.g., the license text) still have very low



(a) Histogram of outlier scores for the CWE-22 identity-map attack.



(b) Precision-Recall curve for the spectral signatures defense.

Figure 4: Example statistics for the spectral signatures defense with $k = 1$ on the small 350M model.**Figure 5: ASR_0 of our directional-map attack against CWE-22 on the 350M model for different number of PCA components.**

outlier scores. We thus suspect that the defense does not actually flag samples based on the presence of the trigger or the bait, but rather attributes higher scores to such samples which appear as (near-)duplicates in the dataset. To substantiate this theory, we run the defense against a dataset used in Section 6.2 which contains (almost) no near-duplicates. Against this adjusted attack, spectral signatures obtain much poorer results: When removing the top 2% of samples based on their outlier scores, we remove only about 1.6% of poisoned samples. To achieve a recall of 80%, we have to remove 86% of the dataset. This affirms our suspicion that spectral signatures merely manage to highlight near-duplicates, rather than finding the samples which contribute to the backdoor. However, the model-specific choice of the correct layer is crucial for the success of the spectral signatures defense and we only evaluate the last hidden state here [41]. It is possible that another representation yields better success. But also note that the defender can not simply pick the layer that works best, as the exact instantiation of the attack is unknown.

Table 12: Results for the spectral signatures defense relating recall (Rec), precision ($Prec$) and removal rates (ϵ).

Att. Bait	k	$\epsilon = 2\%$		Rec = 80 %		Rec = 100 %	
		Rec	Prec	ϵ	Prec	ϵ	Prec
I CWE-22	1	56.05 %	70.38 %	3.23 %	62.22 %	12.64 %	19.86 %
	2	55.60 %	69.82 %	3.24 %	62.06 %	13.39 %	18.75 %
	5	54.50 %	68.44 %	3.30 %	60.91 %	12.49 %	20.11 %
	7	54.98 %	69.04 %	3.24 %	61.93 %	12.95 %	19.40 %
	10	54.81 %	68.83 %	3.27 %	61.47 %	13.10 %	19.17 %
I CWE-916	1	60.57 %	76.07 %	2.64 %	76.07 %	10.41 %	24.13 %
	2	60.40 %	75.86 %	2.65 %	75.75 %	10.76 %	23.34 %
	5	58.88 %	73.94 %	2.69 %	74.63 %	10.87 %	23.11 %
	7	59.24 %	74.39 %	2.70 %	74.39 %	11.07 %	22.68 %
	10	58.54 %	73.51 %	2.72 %	73.98 %	11.06 %	22.71 %
I CWE-89	1	61.71 %	77.50 %	2.58 %	77.78 %	3.55 %	70.69 %
	2	61.54 %	77.28 %	2.59 %	77.58 %	3.56 %	70.63 %
	5	60.79 %	76.33 %	2.62 %	76.81 %	3.64 %	68.98 %
	7	60.85 %	76.41 %	2.61 %	76.90 %	3.64 %	69.07 %
	10	60.49 %	75.96 %	2.65 %	75.79 %	3.64 %	68.91 %
I CWE-22	1	58.08 %	72.94 %	3.00 %	66.93 %	6.41 %	39.15 %
	2	58.04 %	72.88 %	3.02 %	66.61 %	6.42 %	39.09 %
	5	56.99 %	71.57 %	3.10 %	64.82 %	6.65 %	37.77 %
	7	57.50 %	72.21 %	2.95 %	68.03 %	6.45 %	38.91 %
	10	57.04 %	71.63 %	2.97 %	67.66 %	6.52 %	38.51 %
D CWE-916	1	63.79 %	80.10 %	2.52 %	79.76 %	9.01 %	27.88 %
	2	64.01 %	80.39 %	2.53 %	79.52 %	9.21 %	27.27 %
	5	62.82 %	78.89 %	2.57 %	78.09 %	9.35 %	26.85 %
	7	61.77 %	77.58 %	2.58 %	77.99 %	9.54 %	26.34 %
	10	61.94 %	77.78 %	2.61 %	77.04 %	9.58 %	26.22 %
D CWE-502	1	62.36 %	78.31 %	2.60 %	77.23 %	85.45 %	2.94 %
	2	61.76 %	77.56 %	2.61 %	77.03 %	88.45 %	2.84 %
	5	62.10 %	77.98 %	2.62 %	76.78 %	87.79 %	2.86 %
	7	62.24 %	78.16 %	2.65 %	75.76 %	90.94 %	2.76 %
	10	61.80 %	77.61 %	2.67 %	75.25 %	88.45 %	2.84 %
D CWE-327	1	62.67 %	78.70 %	2.54 %	79.02 %	4.09 %	61.39 %
	2	62.85 %	78.92 %	2.56 %	78.58 %	4.11 %	61.10 %
	5	62.50 %	78.49 %	2.58 %	77.92 %	4.10 %	61.27 %
	7	62.33 %	78.28 %	2.59 %	77.50 %	4.12 %	60.95 %
	10	62.61 %	78.62 %	2.58 %	77.80 %	4.07 %	61.71 %
D CWE-295	1	65.64 %	82.43 %	2.45 %	81.87 %	3.91 %	64.30 %
	2	65.73 %	82.54 %	2.45 %	81.87 %	3.90 %	64.34 %
	5	63.77 %	80.09 %	2.49 %	80.76 %	3.93 %	63.93 %
	7	64.63 %	81.16 %	2.49 %	80.70 %	3.95 %	63.64 %
	10	64.44 %	80.92 %	2.51 %	79.97 %	3.90 %	64.47 %
D CWE-79	1	59.38 %	74.57 %	2.88 %	69.78 %	13.97 %	17.98 %
	2	59.54 %	74.76 %	2.92 %	68.88 %	14.00 %	17.93 %
	5	58.21 %	73.11 %	2.98 %	67.31 %	15.15 %	16.57 %
	7	59.10 %	74.21 %	2.89 %	69.45 %	13.52 %	18.57 %
	10	59.21 %	74.36 %	2.89 %	69.61 %	13.70 %	18.34 %
P -	1	31.42 %	39.58 %	67.11 %	3.00 %	99.99 %	2.52 %
	2	32.17 %	40.53 %	63.24 %	3.19 %	99.95 %	2.52 %
	5	32.25 %	40.63 %	62.28 %	3.24 %	99.95 %	2.52 %
	7	32.68 %	41.17 %	59.69 %	3.38 %	99.47 %	2.53 %
	10	32.68 %	41.17 %	59.42 %	3.39 %	99.41 %	2.53 %

Implementation details. In the following we provide additional details on our implementation of spectral signatures. Our implementation of spectral signatures follows Ramakrishnan and Albarghouti [41]. We show a slightly simplified version of the algorithm as pseudocode in Algorithm 2. The defense calculates an outlier score for each sample in the dataset \mathcal{D} , a higher score signaling an increased chance of a sample being poisoned. It is parameterized with the number of top right singular vectors k as well as the fraction ϵ of samples to discard. Greater values of ϵ lead to a higher recall, but also more false positives. Alternatively to the fraction ϵ , a fixed outlier score threshold could be used. First, the model θ needs to be trained or fine-tuned on the full dataset \mathcal{D} consisting of both clean and poisoned data. Then, the mean learned representation \bar{R} across all samples is calculated. The defender can then construct the matrix M consisting of all centered sample representations. The correlation of the centered representations with the k top right

Table 13: Results for the defenses using the per-sample perplexity on the clean pretrained model (S_c), the fine-tuned, poisoned model (S_p) and the per-token perplexity in a poisoned model (S_1). The table relates recall (Rec), precision ($Prec$) and removal rates (ϵ).

Att. Bait		$\epsilon = 2\%$		Rec = 80%		Rec = 100%		
		Rec	Prec	ϵ	Prec	ϵ	Prec	
I	CWE-22	S_c	0.00 %	0.00 %	69.32 %	2.92 %	85.43 %	2.96 %
		S_p	51.50 %	64.67 %	4.61 %	43.54 %	10.96 %	22.92 %
		S_1	0.18 %	0.22 %	82.20 %	2.44 %	96.22 %	2.61 %
	CWE-916	S_c	3.18 %	4.02 %	58.02 %	3.48 %	90.02 %	2.81 %
		S_p	48.56 %	60.98 %	5.74 %	35.03 %	18.87 %	13.31 %
		S_1	11.89 %	14.93 %	74.04 %	2.71 %	92.97 %	2.70 %
	CWE-89	S_c	0.00 %	0.00 %	61.33 %	3.30 %	76.27 %	3.31 %
		S_p	60.35 %	75.78 %	2.76 %	72.86 %	6.29 %	39.91 %
		S_1	0.00 %	0.00 %	87.67 %	2.29 %	98.02 %	2.56 %
D	CWE-22	S_c	0.00 %	0.00 %	67.42 %	3.00 %	85.39 %	2.96 %
		S_p	52.49 %	65.91 %	4.33 %	46.35 %	11.93 %	21.06 %
		S_1	0.89 %	1.12 %	74.18 %	2.71 %	94.89 %	2.65 %
	CWE-916	S_c	2.54 %	3.18 %	62.88 %	3.20 %	90.83 %	2.77 %
		S_p	57.57 %	72.30 %	3.94 %	51.01 %	10.43 %	24.07 %
		S_1	2.50 %	3.14 %	82.48 %	2.44 %	97.15 %	2.59 %
	CWE-502	S_c	0.07 %	0.09 %	58.82 %	3.44 %	81.11 %	3.12 %
		S_p	58.57 %	73.55 %	3.00 %	66.96 %	70.76 %	3.55 %
		S_1	3.88 %	4.87 %	74.75 %	2.69 %	98.22 %	2.56 %
CWE-327	S_c	0.00 %	0.00 %	48.06 %	4.21 %	82.78 %	3.05 %	
	S_p	58.39 %	73.33 %	3.04 %	66.10 %	6.06 %	41.43 %	
	S_1	2.60 %	3.26 %	78.61 %	2.56 %	94.23 %	2.67 %	
CWE-295	S_c	0.82 %	1.04 %	56.81 %	3.56 %	81.37 %	3.11 %	
	S_p	57.88 %	72.69 %	3.15 %	63.85 %	9.58 %	26.21 %	
	S_1	0.01 %	0.01 %	83.44 %	2.41 %	96.37 %	2.61 %	
CWE-79	S_c	2.50 %	3.14 %	72.81 %	2.76 %	92.78 %	2.71 %	
	S_p	47.49 %	59.64 %	4.11 %	48.90 %	38.37 %	6.55 %	
	S_1	0.01 %	0.01 %	79.07 %	2.54 %	96.37 %	2.61 %	
P	-	S_c	2.79 %	3.53 %	69.28 %	2.93 %	99.98 %	2.54 %
		S_p	18.62 %	23.46 %	52.47 %	3.84 %	99.43 %	2.53 %
		S_1	4.39 %	5.53 %	59.73 %	3.37 %	96.75 %	2.60 %

singular vectors of M are then used to obtain the sample outlier scores $s(x)$. The dataset is then sanitized by discarding samples with high outlier scores. Depending on the model architecture and task, choosing a fitting representation function is not trivial. As mentioned earlier, we choose the last hidden state the model generates for a given sample, averaged over token positions (up to 2,048 for CODEGEN models).

Higher number of singular vectors. Related work [41] expand upon the spectral signature defense [47] by considering the top k singular vectors rather than just one. Using multiple singular vectors is beneficial for code models, because the triggers introduce more complex structural changes than in image recognition. In addition to the results for $k = 1$, in Table 12 we show results for k being between 1 and 10. Note how the recall and precision metrics hardly vary by more than 2 %. Thus, in the majority of cases, the correlation with the top singular vector is dominant.

F Details on Perplexity-based Defenses

Table 13 presents the results of our adaptive perplexity-based defenses in three parts: First, columns under “ $\epsilon = 2\%$ ” contain the precision and recall when removing 2 % of the data. Second, columns under “Rec = 80 %” show how many data points need to be removed to reach a recall of 80 % and the corresponding precision. Finally, columns under “Rec = 100 %” show the same for 100 % recall.

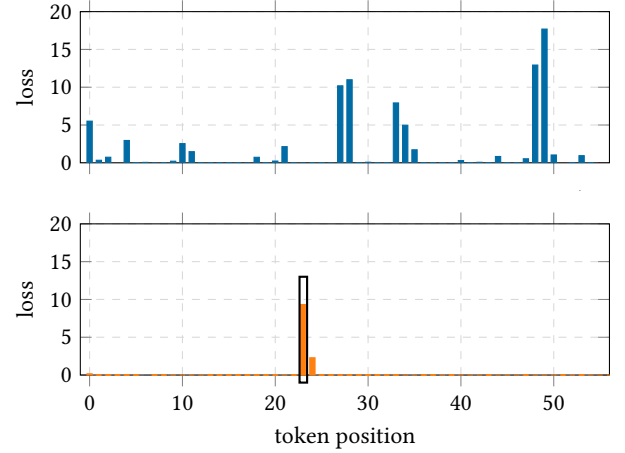


Figure 6: Comparison of per-token loss on a random clean sample (top) and a poisoned sample (bottom). The loss for the randomized token is highlighted with a black frame.

Fig. 6 displays the per-token loss of a single clean sample (top) and a single poison sample (bottom). Our poison samples are characterized by high peaks in low regions. The peak (highlighted with a black frame) represent the randomized token(s) and the low regions the memorized static parts of the near-duplicate poison sample. This can be prevented by using more diverse poison samples as discussed in Section 6.2.

G Tokenizers and Token Embeddings

For the identity-map attack knowing the embedding is irrelevant. For our directional-map attack and our prompt-indexing attack, in turn, knowledge of the tokenizer and token embedding is crucial. However, we experimentally show that even these attacks transfer for similar embeddings. Specifically, our larger models use different embeddings than the attacker knows, which, however, influences attack success marginally. We leave the determination of the exact influence of the tokenizer and the embeddings to future work. Moreover, we speculate that the individual tokenizers and embeddings only differ negligibly as the syntax and vocabulary used in programming languages is relatively constrained and standardized compared to natural language. Below, we discuss the tokenizers used in modern code models.

Tokenizers. The code models Pythia and CodeGen use the same tokenizer as GPT-2 [33, 34, 46]. The exact tokenizer of the OpenAI’s Codex models, however, is not publically available but the embeddings are assumed to be similar to the GPT-3 tokenizer [6]. Google’s Gemini Pro models [3] and the open source CodeGemma models [4], both use the same tokenizer based on Google’s SentencePiece [7], and the Code Llama models uses a similar setting [1] also. In summary, most recent code models use only slightly different tokenizers, most use byte-pair-encoding BPE [44] and unigram language algorithms [24], often based on SentencePiece [7].