Unsafe’s Betrayal: Abusing Unsafe Rust in Binary Reverse Engineering via Machine Learning

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Abstract
Memory-safety bugs introduce critical software-security issues. Rust provides memory-safe mechanisms to avoid memory-safety bugs in programming, while still allowing unsafe escape hatches via unsafe code. However, the unsafe code that enhances the usability of Rust provides clear spots for finding memory-safety bugs in Rust source code. In this paper, we claim that these unsafe spots can still be identifiable in Rust binary code via machine learning and be leveraged for finding memory-safety bugs. To support our claim, we propose the tool rustspot, that enables reverse engineering to learn an unsafe classifier that proposes a list of functions in Rust binaries for downstream analysis. We empirically show that the function proposals by rustspot can recall 92.92% of memory-safety bugs, while it covers only 16.79% of the entire binary code. As an application, we demonstrate that the function proposals are used in targeted fuzzing on Rust packages, which contribute to reducing the fuzzing time compared to non-targeted fuzzing.

1 Introduction
Memory-safety issues have been a serious focus of a security community. Among the hundreds of bugs being reported annually, around 70% are potentially exploitable memory-safety bugs based on reports by Microsoft [55] and Google [25]. These exploitable issues enable attackers the ability to read and write to the memory, triggering critical vulnerabilities (e.g., privilege escalation in the Linux kernel [46]). Although many bug patterns (e.g., use-after-free, double-free, and buffer overflow) have been deeply studied by researchers, the number of bugs identified every year rarely changes.

Rust, as a system programming language, is proposed to address these memory-safety issues [81]. The key idea of Rust’s memory safety is to break the code into two: safe and unsafe Rust. In particular, the safe Rust is a well-typed program that guarantees memory safety during compile-time based on two key concepts: ownership and borrowing. Ownership is a constraint that a value cannot be owned by more than one variable at the same time. Based on this constraint, the compiler takes over the lifetime of the variable and automatically frees it when its lifetime ends (e.g., the owner variable goes out of scope). Because of this, memory-safety issues like use-after-free or double-free bugs can be avoided. Borrowing is the concept that a reference to a variable is borrowed without having the ownership of the variable. There are two types of borrowing; a mutable reference allows programmers to mutate a variable’s value, and an immutable reference only grants read permission. For each variable, Rust restricts having only one mutable reference or multiple immutable references; from this restriction, data race or memory corruption is eliminated during compilation.

However, these two restrictions may stop programmers from building a program that they intended to or having performance losses. Unsafe Rust is used to temporarily break these restrictions and transfer the responsibility from the compiler to programmers to ensure memory safety. Specifically, it allows programmers to do unsafe operations [82] (e.g., dereferencing a pointer or calling external library functions), so it is a programmer’s task to ensure the memory safety of the

Figure 1: rustspot can aid reverse engineering to recall 92.92% of bugs by only covering 16.79% of instructions; baselines require higher coverage rates to achieve similar bug recall rates.
program with these unsafe superpowers.

The mixture of safe and unsafe Rust provides a memory-safety guarantee while enabling its usability for various purposes, including system programming. However, Rust is not a silver bullet. Recently, Rudra [7] demonstrated that it finds a large number of memory-safety bugs in the Rust ecosystem by leveraging unsafe blocks as buggy spots. This observation opens possibilities for Rust binary reverse engineering; it can abuse the unsafe code in binaries to efficiently localize memory-safety bugs without massive effort in auditing the entire binaries.

In this paper, we claim that unsafe code in Rust binaries is detectable via machine learning; thus, the binary code analysis effort in reverse engineering is significantly reduced in finding memory-unsafe bugs. In particular, we prove our claim by demonstration via our tool rustspot. It takes as input a set of Rust binaries like static executables or libraries and proposes a list of functions based on the likelihood of being unsafe functions1, where reverse engineering tools should first look to find memory-unsafe bugs. Figure 1 shows that the function list provided by rustspot contains 92.92% of memory-safety bugs, while the number of instructions to be covered is only 16.79% of the entire instructions in binaries. As an application, the function proposals from rustspot can be used with targeted fuzzing. We demonstrate that the targeted fuzzing guided by the function proposals can reduce analysis time by 49.7% to find a similar number of bugs compared with non-targeted fuzzing. In short, unsafe Rust, which is devised to enable safe Rust to be memory safe, can help reverse engineering reduce the analysis effort in finding security-critical memory-unsafe bugs.

The proposed tool rustspot overcomes three technical challenges. First, considering that the memory-safety bugs appear in a tiny portion of functions in binaries, finding bugs is statistically challenging [98]. Consequently, we exploit the strong correlation between unsafe Rust and memory-safety bugs [94, 68, 7] and transform the problem into finding unsafe functions in Rust binaries. Since unsafe functions appear more frequently in code than buggy functions, learning unsafe function patterns is statistically feasible.

Second, to learn and evaluate unsafe function patterns, clean datasets are required. In Rust source code, unsafe blocks, unsafe functions, and bug-annotated code lines are clearly visible, but after compilation, these annotations disappear. To address this issue, we exploit DWARF debugging information and a customized Rust toolchain to precisely localize unsafe regions within unsafe Rust and project the unsafe regions into binary instructions. As for the buggy annotations, we similarly treat them as unsafe regions to automatically generate the mappings to binaries based on DWARF information. Based on this label projection to binaries, we generate two datasets for learning and evaluation: Crate and RustSec datasets. The unsafe labels on functions from Crate and RustSec datasets are automatically generated by compiling commonly used Rust packages, where the dataset contains a set of functions in binaries, each of which has unsafe labels. The bug labels from the RustSec dataset are required to manually read the bug report and label the buggy lines in source code. Then, our label generator can take this information and map a line annotation into the location in binary instructions.

Finally, based on the Crate and RustSec datasets, we learn and evaluate an unsafe classifier. In particular, if the unsafe classifier returns “unsafe,” the corresponding function is considered to have memory-safety bugs because of the strong correlation between unsafe code and memory-safety bugs. We later evaluate this classifier over the RustSec dataset, the result of which is shown in Figure 1. When applying our unsafe classifier in practice, one technical challenge is how to choose the threshold of a classifier to provide a list of functions for reverse engineering. We provide a novel algorithm to choose the threshold that comes with the correctness guarantee on the recall of the unsafe classifier over unsafe functions.

Our contributions are summarized as follows:

• We propose a way to automatically generate datasets, i.e., Crate and RustSec datasets, for learning and evaluating an unsafe classifier2.

• We propose unsafe classifier learning and thresholding algorithms that leverage the strong relation between unsafe code and memory-safety bugs to efficiently detect the bugs in Rust binaries.

• We demonstrate that the proposed approach aids reverse engineering to scale down the search space for finding the memory-safety bugs in Rust binaries, via evaluating the unsafe classifier on the RuseSec dataset and applying it on targeted fuzzing.

2 Background

Safe rust. Rust language [54] provides a memory-safety guarantee during compile time, while allowing control over low-level access to resources. The claimed memory-safety guarantee is proved in [70, 49] under some assumptions on language models. Here, we describe the key concepts to achieve the memory-safety: ownership and borrowing. By applying these two concepts of static analysis, safe Rust guarantees that there are no undefined behaviors in compiled programs [70].

Ownership is a relation between a value and a variable; each value in Rust is owned by only one variable, and memory associated with the value is automatically freed if the variable goes out of scope. This simple memory management mechanism provides a compile-time memory safety without having a run-time garbage collector. In particular, since a value is automatically freed via drop(), added by a compiler,
memory leakage due to programmers’ mistakes is naturally avoided. Moreover, a value, which can be a pointer to heap memory, is owned by only one variable; thus, its associated memory is freed only via \texttt{drop()}, by which double-free bugs are avoided. Although the ownership provides a vital safeguard to avoid memory-safety bugs, it is too strict to have only one owner for each value. Thus, borrowing is introduced to address this issue.

Borrowing allows having a reference to a variable without ownership. Specifically, Rust provides two types of borrowing: immutable and mutable. Each variable can have either multiple immutable references or only one mutable reference. Through this restriction, safe Rust ensures that no other party will have write access to the variable when it has been borrowed as a mutable reference.

\textbf{Unsafe rust.} Although safe Rust provides a strong guarantee on the memory safety and relatively flexible restrictions, there are many cases in which programmers need to maintain a shared mutable reference in system programming. For example, memory can be shared among multiple threads with well-defined synchronization. Also, reference counting is widely used under system memory management. To support such cases, unsafe Rust is introduced to escape from the Rust compiler’s check inside safe regions and requires programmers to ensure the memory safety inside the unsafe regions. In particular, Rust defines five operations as unsafe operations [82], which help programmers to identify unsafe regions and ensure memory safety. As these memory-related operations within unsafe regions are not checked by a compiler for memory safety, they are likely to cause memory-safety bugs. In this work, we exploit this relation between unsafe regions and memory-safety bugs to localize the bugs in Rust binaries.

### 3 Unsafe Function Classification

The ultimate goal in finding memory-safety bugs is to design a classifier that discriminates each function in binaries to check whether it contains a memory-safety bug: we call the classifier a bug classifier. In particular, let \( x \in X \) be a function represented in binary code, \( y \in \mathcal{Y} := \{0, 1\} \) be a bug label, where \( y = 1 \) means “bug,” and \( \hat{y} : X \rightarrow \mathcal{Y} \) be the bug classifier, which returns a predicted bug label on \( x \). In this paper, we consider the following construction of a bug classifier:

\[
\hat{y}(x; S_{\text{prop}}) = \begin{cases} 
  f(x) & \text{if } x \in S_{\text{prop}} \\
  0 & \text{otherwise}
\end{cases},
\]

where \( f : X \rightarrow \mathcal{Y} \) is a fuzzing algorithm, which uses a function \( x \) to find bugs, and \( S_{\text{prop}} \) is a set of functions that likely have bugs, which we call a proposal set; thus, the bug classifier \( \hat{y} \) selectively runs the fuzzing algorithm based on the given proposal set. In designing the bug classifier \( \hat{y} \), the main challenge is the analysis time in finding bugs. In particular, a generic fuzzing algorithm [26] needs to generate a huge number of inputs of all target functions to trigger all parts of functions.

To overcome this issue, our goal is to spot a small proposal set \( S_{\text{prop}} \) that likely contains memory-safety bugs to reduce the entire analysis time. We exploit a strong correlation between memory-safety bugs and unsafe functions in Rust (i.e., memory-safety bugs are triggered by unsafe functions under some conditions) and design an unsafe function classifier \( \hat{u} : X \rightarrow \{0, 1\} \), where \( \hat{u}(x) = 1 \) means \( x \) is an unsafe function, for the small proposal set, i.e., \( S_{\text{prop}} = \{ x \mid \hat{u}(x) = 1 \} \). As we consider \( \hat{u} \) as a proposal function to generate the proposal set for the bug classifier, we also denote the bug classifier as a function of \( \hat{u} \), i.e., \( \hat{y}(x; \hat{u}) \). Figure 2 summarizes our assumptions and problem along with a proposed approach, rustspot, which consists of data generation and unsafe function classifier learning. In the following, we describe the details on assumptions and our problem.

#### 3.1 Assumptions and Problem

\textbf{Environment.} To learn the unsafe classifier, we consider a variant setup of the domain adaption [9, 23] in machine learning. In particular, the domain adaptation considers two distributions: source and target distributions, where labeled examples are drawn from the source, but unlabeled examples are drawn from the target; the examples from the source and target are used to learn a classifier, but labeled examples from the target are only used for evaluation. However, we consider that “weakly” labeled examples are drawn from both source \( \hat{P} \) and target \( \hat{Q} \). Here, the “weak” label means a label that has a strong correlation to an original label; thus, “weakly” labeled source and target examples are used to learn a classifier. The following describes the definition of “weak” label in the context of bug classification.

In Rust memory-safety bug classification, the original source is a distribution over Rust packages. Similarly, the original target is a distribution over Rust packages, but it is chosen by a binary analyzer from which the analyzer finds memory-safety bugs (as shown in Figure 2). For the original source and target distributions, we consider induced distributions from which “weakly” labeled examples are drawn. In our case, the “weak” labels are unsafe annotations on code blocks or functions in Rust source code. The reason that unsafe labels are called “weak” labels stems from the fact that unsafe functions can trigger (but not always) memory-safety bugs, thus an unsafe label on a function provides a weak signal that the function may be related to the memory-unsafe bugs. See Section 3.2 for details on the definition of memory-safety bugs in Rust binaries and its relation to unsafe blocks.

The memory-safety bugs of our interest may be triggered by other components, e.g., a Rust compiler [29, 83], SQLite backend [35], or the standard C library [33], but we assume that the memory-safety bugs are only due to the misuse of the
**Rust language within Rust packages.**

**Assumption 1.** A Rust compiler or underlying external libraries (e.g., the standard C library or SQLite) of Rust packages are correct and do not have memory-safety bugs that can be propagated to Rust packages.

**Programmer.** The Rust binary to be analyzed is generated by a programmer, which potentially includes memory-safety bugs. Here, we consider two key assumptions on the binary generation process and binary post-processing process. First, the binary analyzer does not have capabilities to generate the binaries provided by a programmer, and the generated binaries are from the unit tests in the case of Rust libraries.

**Assumption 2.** A Rust package is compiled into stripped binary files where compile options are unknown to a binary analyzer. If the package generates a Rust library, executables generated from its unit tests are provided as binary files.

Additionally, in the binary post-processing process, we assume that the function boundaries of the binaries are given, which can instead be predicted with high accuracy [42, 74, 50], and also functions defined by a package-programmer are known and only considered for analysis, which can be achievable via library isolation tools [43].

**Assumption 3.** The function boundaries of target binaries are known, and functions from non-libraries are considered.

Based on these assumptions, we consider a function \( x \) that is drawn from a target distribution over functions \( Q_x \).

**Binary analyzer.** A binary analyzer desires to find a specific type of memory-safety bugs by choosing a target distribution (e.g., Rust packages known to have bugs). In general, collecting buggy Rust packages and isolating the bug location in the packages is expensive; thus, we consider that the analyzer does not have access to buggy labels but only allows access to a few Rust packages from the target distribution. Due to this limited access to the target distribution, the analyzer leverages data from a usual Rust package distribution for the source of obtaining a larger number of unsafe labels. Along with access to the source and target packages, the binary analyzer has access to source code, so it has capabilities to modify the code and compile it with various options. Also, the analyzer aims to find bugs in package-programmer defined functions in Rust packages, which is a common practice to guide reverse engineers to avoid library functions [43].

In short, from the Rust source code compilation and the unsafe labels within the source code, the binary analyzer generates functions in binary along with unsafe labels. We denote the distribution over unsafe labeled functions from the source or target by \( \tilde{P} \) or \( \tilde{Q} \), respectively. Only for evaluation purposes, we consider a conditional distribution over bug labels given a function \( x \) from the target, denoted by \( \tilde{Q}_{y|x} \). Note that we consider that the bug labels used for evaluation are given by experts (e.g., bug reports) and that \( Q := Q_x \cdot \tilde{Q}_{y|x} \).

**Problem.** We find an unsafe classifier \( \tilde{u} \) to aid a bug classifier \( \tilde{y} \). In particular, a bug classifier needs to have the smallest list of functions that embeds the desired number of buggy functions to focus only on a few functions to reduce running time for fuzzing. To evaluate the performance of the unsafe classifier, we define recall (for measuring efficacy) and coverage (for measuring efficiency) of the unsafe classifier. The recall is the ratio of predicted unsafe functions to the total number of true buggy functions, i.e.,

\[
\mathbb{P}_{(x, y) \sim \tilde{Q}} [\tilde{u}(x) = 1 \mid y = 1].
\]

To measure the efficiency, we first consider an efficiency metric \( S : X \rightarrow \mathbb{R} \) of a function, which we will use the size of a function by counting the number of instructions, including instructions in callees. Then, the coverage is the normalized, expected size of functions when the classifier predicts it as an
unsafe function, i.e.,

\[
\mathbb{E}_{x \sim Q^*} [S(x)] / \mathbb{E}_{x \sim Q^*} [S(x)],
\]

where \( S(x) := S(x)x(\hat{u}(x) = 1) \) is the size of a function \( x \) when \( \hat{u}(x) = 1 \).

Based on the recall and coverage, we define our problem as follows: given \( \varepsilon \in (0, 1) \) and \( \delta \in (0, 1) \), find \( \hat{u} \) that probably satisfies desired recall, i.e., with probability at least \( 1 - \delta \),

\[
\mathbb{P}_{(x,y) \sim Q} [\hat{u}(x) = 1 | y = 1] \geq 1 - \varepsilon,
\]

while minimizing coverage. Here, \( \hat{u} \) is learned using \( m \) unsafe labeled functions from the source, i.e., \( S \sim \mathcal{P}^m \), and \( n \) unsafe labeled functions from the target, i.e., \( T \sim \hat{Q}^n \). We can also say that \( \hat{u} \) is probably approximately correct (PAC) with respect to our recall metric, where classification error is frequently used in a PAC learning framework [85]. Section 4 describes how to generate unsafe and buggy labeled functions, and Section 5 explains how to learn \( \hat{u} \). In the following, we provide details on the definition of the memory-safety bugs in Rust binary, which plays a crucial role in generating buggy labeled functions and provides the strong relation to unsafe functions.

### 3.2 Memory-safety Bug in Rust Binaries

To evaluate an unsafe classifier, we rely on bug-labeled functions generated from Rust packages. In particular, we emphasize that labeling bug functions requires a well-defined notion on memory-safety bugs. In general, defining the memory-safety bug is challenging [44, 6]. However, we define the memory-safety bugs in the Rust context by leveraging the compile-time memory-safety guarantee of Rust, assuming safe Rust provides a safety guarantee by its compiler (which is also partially proven in [70] on a simplified Rust type system), and by exploiting the fact that the memory-safety bugs are strongly related to Rust unsafe blocks.

**Definition.** Given memory-safety bugs reported in RustSec Advisory [27], our purpose of defining the memory-safety bugs is to localize source code lines that are possibly related to memory-safety bugs and label these lines for generating a dataset. To this end, we exploit the Rust memory-safety bug definition in [7]. In particular, we adapt their state machine interpretation. For example, Definition 3.1 of [7] says “A function \( F \) has a panic safety bug if it drops a value \( v \) of type \( T \) such that \( v \notin \text{safe-value}(T) \) during unwinding and causes a memory safety violation.” This is interpreted that the behavior of the function \( F \) affects the state of memory (i.e., the value \( v \)) that leads to the memory safety violation.

However, considering the difficulty of defining the memory-safety bugs and the difference in setups, we propose to define bugs in our own notations instead of directly using the previous definition. In particular, the definitions in [7] are defined over source code level, but we are considering binary code. Moreover, Send/Sync variance bugs in Definition 3.3. of [7] are associated with a Rust-type system; this type of bugs generally cannot be captured in binaries, thus we do not use the definition. However, to validate the reliability of our definition, we inductively check whether our definition can be used to describe known bugs, mainly found by [7].

To define the memory-safety bugs, we first leverage the observations that Rust code without unsafe blocks is memory-safe, assuming that a Rust compiler is correct (Assumption 1), which is also proven to be valid under a Rust-equivalent-type system [70, 49]. If the Rust compiler is incorrect, anything can happen, e.g., converting a reference with any lifetime into a reference with static lifetime [29], which could lead to memory-safety bugs. From this, we consider that code having an unsafe block is a necessary condition on code having a memory-safety bug. However, this condition is not sufficient; thus, we consider the concept of “unsafe states.”

In particular, we simplify a program running on a machine as a state machine. Here, \( S \) is a set of states, and \( A \) is the power set of instructions by which a state is changed. The set of states \( S \) could be simply all possible states of memory (including registers). However, we consider higher-abstraction on the memory by viewing the states as a list of variables, where \( T \) is a set of types, and a variable is a pair of a type \( V \in T \) and a value \( v \in V; \) thus, \( S := (T \times V)^* \). The power set of instructions \( A \) contains a sequence of instructions \( \pi \in A \); we denote the \( i \)-th instruction in the instruction sequence by \( \pi_i \) and denote a subsequence from the \( i \)-th instruction to the \( j \)-th instruction by \( \pi_{i,j} \). If a sequence of instructions is a function, we denote it as \( \lambda \in A \). Given a state \( s \in S \) and a sequence of instructions \( \pi \in A \), the state is changed to \( s' \) by applying the instructions from the state, i.e., \( s' := \mathcal{T}(s, \pi) \), where we denote the state transition function by \( T : S \times A \rightarrow S \).

To define a memory-safety bug, we define a term called a safe-type \( V_{\text{safe}} \in T \) (where a safe-value in [7] is included). In particular, we consider a subclass of bugs that is associated with a mismatch between a type \( V \) and a safe-type \( V_{\text{safe}} \). Here, we highlight that the safe-type is different than a syntactic type \( V \) of the value in Rust; the safe-type of a value is a type that a programmer intends to associate with the value. If a value is not in the safe-type, i.e., \( v \notin V_{\text{safe}} \), we say the current state \( s \) is unsafe, i.e., \( s \notin S_{\text{unsafe}} \), where \( S \) is partitioned into unsafe states \( S_{\text{unsafe}} \) and safe states \( S_{\text{safe}} \). For example, a programmer assumes that a variable contains a pointer \( v \), but if the pointer is unintentionally freed, the value in the variable is not the safe type, i.e., \( v \notin V_{\text{safe}} \) as the value is pointing to an invalid address. Later, the programmer wants to free this pointer since the pointer \( v \) should be a safe type for the programmer’s perspective, but, this is double-free. As in this example, given a safe-type definition, we immediately know when the state changes to unsafe, i.e., when \( v \notin V_{\text{safe}} \) occurs.

Given Rust unsafe blocks, safe types, and unsafe states, we define a memory-safety bug in Rust binaries. In particular, we...
say a function has a memory-safety bug if the instructions of the function change the current state from safe to unsafe due to a Rust unsafe block.

**Definition 1** (memory-safety bugs in Rust binaries). We say a function \( h_{i,j} \) has a memory-safety bug with respect to unsafe states \( S_{\text{unsafe}} \) if for some \( s_i \in S_{\text{safe}} \) and \( t \in \{i, \ldots, j\} \) we have
\[
T(s_i, \lambda_t) \in S_{\text{unsafe}},
\]
and \( \lambda_j \) for \( j \in \{i, \ldots, t\} \) is included in a Rust unsafe block.

Here, the memory-safety bug definition relies on unsafe states \( S_{\text{unsafe}} \). We consider \( S_{\text{unsafe}} \) where a state in it eventually triggers one of four concrete memory safety bugs in Figure 3, where the most RustSec reports [27] are related to these bugs.

In Rust, memory-safety bugs are mostly covered by an umbrella term called undefined behaviors [80]. In the following, we claim that our definition of memory-safety bugs can cover known memory-safety bugs that are also covered by undefined behaviors, as shown in Figure 3; thus, our definition is likely a good guideline for labeling memory-safety bugs.

**Undefined behaviors.** Undefined behaviors in Rust are code rules, each of which makes Rust code incorrect [80]. In this paper, we consider a subset of undefined behaviors, i.e., undefined behaviors that eventually trigger memory-safety bugs in binaries. In particular, by assuming the correctness of a Rust compiler, we believe that all memory-safety bugs, which includes bugs in our memory-safety bugs definition, trigger undefined behaviors considered in Rust, as shown in Figure 3. Moreover, our memory-safety bug definition does not cover some bugs that trigger undefined behaviors, e.g., a Send/Sync variance bug that usually introduces data race.

The following is a list of undefined behaviors that are known to introduce memory-safety bugs: (1) producing an invalid value at its respective type, (2) accessing to uninitialized memory, and (3) violating Rust borrowing rules. We explain how each undefined behavior can lead to known memory-safety bug examples (e.g., double-free, use-after-free, uninitialized variables, memory corruption, or memory exposure) and how these memory-safety bug examples are interpreted and labeled under **Definition 1**. See additional examples in Appendix B.

**Producing an invalid value.** In Rust, we say that code produces an invalid value with respect to its type if the value is not strictly in the type; this undefined behavior is common in Rust [27]. Technically, having an invalid value does not introduce memory-safety bugs if it is not used. However, Rust’s default panic handler will try to release all the memory controlled by the compiler; thus, these invalid values eventually can be used when panic occurs.

**Example 1** (producing an uninitialized variable potentially leads to memory corruption). *Listing 1* demonstrates one undefined behavior: producing an uninitialized variable. Here, \( T::\text{clone}() \) is user-provided and can potentially panic. If the panic occurs during the \( \text{vec} \) initialization loop, the \( \text{vec} \) will be partially initialized. The uninitialized part of \( \text{vec} \) becomes the invalid value. When the default panic handler tries to free \( \text{vec} \)'s memory, the uninitialized part will be dropped, potentially leading to memory corruption. Therefore, after executing the instructions in Line 8, the program state \( s \) transfers to \( S_{\text{unsafe}} \); we annotate Line 8 as buggy.

### 4 Dataset Generation for Rust Binaries

To train a classifier for unsafe functions in Rust, we first need reliable datasets. In this section, we explain how we prepare two datasets: Crate and RustSec datasets. Table 1 summarizes the dataset statistics in the number of functions in binaries along with their labels. In short, our datasets contains 16M labeled functions; the following sections include the details.
4.1 Crate Dataset: CrateU

The Crate dataset contains two parts: a list of Rust functions in binaries and labels for each function. The dataset is generated from all the Rust crates from crates.io⁴. For each crate, we compile it with a customized toolchain, which can automatically generate unsafe labels during compilation. Cargo has Edition 2021, which enables the crate to be backward incompatible. Unfortunately, cargo doesn’t provide an automatic migration tool for this new feature [19], so our toolchain can’t handle this error automatically for incompatible crates and ignore the crates during the compilation. Besides, our toolchain tries to compile these crates into ELF binaries, using either example binaries or tests to build target binaries. Therefore, for those crates only containing macros, our dataset doesn’t include them. After these filters, our toolchain finally generates binaries and labels for 24,631 crates with 77,347 binaries among 74,382 crates. For each instruction inside the compiled binaries, a label indicating whether it is inside an unsafe block as well as its unsafe type is generated. We consider 14 different unsafe types, defined in Table 2 to support more fine-grained analysis. In particular, the 13 unsafe types are internally defined in the Rust compiler, marked as predefined in Table 2. We additionally add one more unsafe type, UnsafeFunction, to annotate Rust unsafe functions, i.e., unsafe fn as a function annotated by UnsafeFunction may not contain unsafe blocks (e.g., set_len() of the Rust standard Vec library).

Crate dataset statistics. The novel Crate dataset, denoted by CrateU, is a set of the pair of a function in binary and the corresponding unsafe labels, i.e., \( S := \{ (x_1, u_1), \ldots, (x_m, u_m) \} \sim \mathcal{P}_n \), where \( x_i \) is a function in binary, \( u_i \) is a set of unsafe labels (e.g., \{0\} for “safe” and \{1,2\} for “unsafe” with the ID 1 and 2 in Table 2), \( m \) is the total number of the function and label pairs. Table 1 shows a summary of the number of unsafe labeled functions collected from Rust packages. As can be seen, the number of functions with unsafe labels is about 15.7M, which is large enough for training and evaluation purposes.

Figure 4 shows summaries on the different aspects of the Crate dataset. In particular, its unsafe type and size distributions are illustrated in Figure 4(a) and Figure 4(b), respectively. Here, the size is measured by the number of instructions in a function, including its callees.

Table 1: Dataset statistics in the number of functions

| Label   | Crate   | RustSec |
|---------|---------|---------|
| safe    | 15,407,579 (97.58%) | 428,157 (95.65%) |
| unsafe  | 382,743 (2.42%)     | 19,488 (4.35%)   |
| no-bug  | -       | 447,405 (99.95%) |
| bug     | -       | 240 (0.05%) |

As shown, the dominant number of functions has unsafe types CallToUnsafeFunction, UnsafeFunction, and DerefOfRawPointer. The CallToUnsafeFunction label means that a original function contains an instruction that calls an unsafe function. This implies that learning a pattern for the unsafe function is crucial to correctly classify the original function as “unsafe.” Moreover, considering the corresponding size distribution, the most functions consist of at least 10 instructions; this improves the possibility to learn an unsafe pattern of each function.

Automatic unsafe label generation. We use DWARF debugging information and our customized Rust toolchain to build our automatic label generator for rustspot. The toolchain consists of two parts: a specialized compiler to figure out the precise region of unsafe blocks (including Rust unsafe functions) and a binary parser to analyze output binaries. We modify the Rust compiler to record the precise location of unsafe blocks in source code during compilation. Internally, the Rust compiler will perform unsafe checks on the input source code to ensure that all the unsafe operations are captured by a programmer. We extract such information and record them during compilation.

Then, we build our binary parser based on the DWARF debugging information [20] generated by the Rust compiler. We modify configuration files for each Rust package to add debugging output for all compilation targets. Our binary parser will utilize this information to match each instruction back to its source code location and then compare it with the unsafe regions recorded by the Rust compiler to generate the labels. Although our rustspot aims to generate the most precise and complete labels, due to the limitations of the DWARF debugging format, it has the following challenges.

Inline function and procedural macros. Function inlining is a popular way for optimization widely used in the Rust community. However, the state-of-art DWARF debugging standard only marks the instructions of an inline function to its caller’s source location, thus failing to map it back to the inline function itself. Consequently, our binary parser could miss such unsafe blocks inside an inline function. To address this issue, we build a preprocessor to remove all mandatory inline flags in the source code and disable Rust compiler’s automatic inlining. However, our tool does not handle procedural macros; see limitations in Section 7 for details.

4.2 RustSec Datasets: RustSecU and RustSecB

To evaluate the effectiveness of a unsafe classifier in finding bugs, we create a novel memory-safety bug dataset that contains real memory-safety bug cases from the RustSec Advisory Database [27].

RustSec Advisory Database. The RustSec Advisory Database [27] includes bug reports from Rust packages. In
Given a RustSec advisory report, we automatically 
generate buggy label files during the compilation process. 
Such a report contains a detailed discussion on bug analyses 
in the form of GitHub issues. Based on these reports, we 
manually identify the lines of code that make a program state 
unsafe, as in Definition 1. Finally, we apply our rustspot to 
automatically generate buggy label files for each function 
and project each buggy label to a function in a binary file. 
Note that this process is the same as unsafe-label generation 
except that buggy code lines are given instead of 
unsafe code lines. In addition to generating bug-labeled 
functions, we also generate unsafe-labels for each function, as 
mentioned in Section 4.1.

**RustSec dataset statistics.** The novel RustSec dataset is a set 
of the tuple of a function in binary, unsafe labels, and a bug 
label, i.e., \{(x_1, u_1, y_1), \ldots, (x_n, u_n, y_n)\}, where \(x_i\) is a function 
in binary, \(u_i\) is a set of unsafe labels as before, \(y_i\) is a bug label, 
and \(n\) is the total number of the labeled functions. Here, we 
denote a distribution over labeled functions only with bug 
lables by \(Q\) and a distribution over labeled functions only 
with unsafe labels by \(\bar{Q}\), as mentioned in Section 3. Moreover, 
we denote the samples drawn from \(Q\) and \(\bar{Q}\) by RustSecB 
and RustSecU, respectively.

Table 1 shows the summary of the number of labeled functions. 
As expected, the number of buggy functions is tiny, i.e., 240, 
compared to the total number of functions. Figure 5 shows 
summarizes of the different aspects of the unsafe-labeled 
functions in RustSecU; the major trend is similar as before 
in Figure 4, except that a distribution over unsafe types is 
shifted, i.e., the functions in RustSecU contain more external 
function calls than CrateU. In general, this means a func-
5 Unsafe Function Classifier Learning

The major challenge of learning the bug classifier directly is the lack of bug labels. We leverage the strong correlation between memory-safety bugs and unsafe blocks in Rust, as shown in Definition 1, thus focusing on classifying whether each function embeds unsafe code. Here, we propose to learn unsafe function classification is to design a classifier that predicts whether a given function embeds unsafe blocks or itself is a Rust unsafe function. In particular, let $x \in X$ be function instructions represented in assembly code, including assembly code of callees by adding special tokens (i.e., $\llcorner \text{C} \rceil$) proportional to call depth; let $U := \{1, \ldots, J\}$ be a set of unsafe labels, where $J$ is the total number of unsafe types (i.e., $J = 14$ as in Table 2), $u \in 2^{\mathbb{R}_{\geq 0}}$ be a subset of safe or unsafe labels, $\delta : X \times U \cup \{0\} \rightarrow \mathbb{R}_{\geq 0}$ be an unsafe score function, and $\hat{\delta} : X \rightarrow \{0, 1\}$ be the unsafe classifier. Lastly, labeled functions from source and target distributions are split into train, validation, and test sets, i.e., $S := (S_{\text{train}}, S_{\text{val}}, S_{\text{test}})$ and $\hat{F} := (\hat{F}_{\text{train}}, \hat{F}_{\text{val}}, \hat{F}_{\text{test}})$, where each set consists of unsafe labeled functions $(x, u)$. In this paper, we consider the following parameterization of the unsafe classifier:

$$\hat{u}(x) := \begin{cases} 1 & \text{if } 1 - \hat{s}(x, 0) \geq \hat{\tau} \\ 0 & \text{otherwise} \end{cases}$$

Here, $\hat{s}(x, 0)$ is the safe score of a given function $x$, and $\hat{\tau} \in \mathbb{R}_{\geq 0}$ is a threshold of the unsafe classifier; thus, if the unsafeness $1 - \hat{s}(x, 0)$ is larger than a threshold $\hat{\tau}$, we consider that a function $x$ is unsafe. In the following, we describe how to learn $\hat{u}$ via learning $\hat{\delta}$ and $\hat{\tau}$ with probably approximately correct (PAC) guarantee on the recall of $\hat{u}$.

5.1 PAC Thresholding

The unsafe classifier $\hat{u}$ is parameterized by $\hat{\delta}$ and $\hat{\tau}$; $\hat{\delta}$ can be a neural network trained by minimizing the multi-label loss, which will be described in Section 5.2. Here, suppose $\hat{\delta}$ is given and consider how to choose $\hat{\tau}$ with PAC guarantee.

In particular, choosing a threshold of a classifier is a classical problem [62], where heuristic methods are mostly considered. Here, we consider a rigorous thresholding approach that comes with PAC guarantee based on PAC prediction sets [87, 89]. In particular, our problem of choosing a threshold is reduced to constructing the PAC prediction set; thus, the same algorithm is used for selecting the threshold $\hat{\tau}$. In the following, we provide an algorithm to choose a threshold and prove its PAC guarantee on recall.

Algorithm. We adopt the PAC prediction set algorithm [59, 60] for thresholding. Let $\hat{\theta}$ be the upper Clopper-Pearson (CP) bound [12], where the binomial parameter $\mu$ is included with high probability, i.e., $\hat{\theta}(k; m, \hat{\delta}) := \sup \{ \theta \in [0, 1] | F(k; m, \theta) \leq \hat{\delta} \} \cup \{1\}$, where $\mathbb{P}_{k \sim \text{Binomial}(m, \theta)}[\mu \leq \hat{\theta}(k; m, \hat{\delta})] \geq 1 - \hat{\delta}$. Here, $F(k; m, \theta)$ is the cumulative distribution function of the binomial distribution with $m$ trials and success probability $\theta$. The threshold $\hat{\tau}$ is obtained by solving the following optimization for the threshold $\hat{\tau}$:

$$\hat{\tau} = \arg \max_{\tau \in \mathbb{R}_{\geq 0}} \tau \quad \text{subj. to} \quad \hat{\theta}(k; |\hat{F}_{\text{cal}}|, \hat{\delta}) \leq \varepsilon, \quad (2)$$
We first demonstrate the efficacy of our tool rustspot by evaluating a unsafe classifier $\hat{u}_{\text{RustSecU}}$ over RustSecB, where the classifier is learned over CrateU and RustSecU. The empirical evaluation shows that learning unsafe code patterns in Rust binaries is feasible, and recognizing unsafe code aids reverse engineering to discover a desired number of memory-safety bugs by only reviewing a small amount of binary code. The following includes details of our experiment setup.

We then applied our unsafe classifier on popular crates and applications to show its efficiency. Specifically, we combine our unsafe classifier $\hat{u}_{\text{CrateU}}$ with cargo fuzz to guide the fuzzing process. We empirically show the efficiency of our unsafe classifier in fuzzing by finding a similar number of bugs while reducing analysis time by 20.5% compared with fuzzing without any guidance. We also applied our model on famous rust binaries (including a Servo web browser, a secure web engine written in Rust developed by Mozilla) to evaluate unsafe classification performance.

6 Evaluation

We first demonstrate the efficacy of our tool rustspot by evaluating a unsafe classifier $\hat{u}_{\text{RustSecU}}$ over RustSecB, where

where $T_{\text{cal}}$ is the set of unsafe functions in $T_{\text{val}}$, i.e., $T_{\text{cal}} := \{(x, u) \in T_{\text{val}} \mid u \neq \emptyset\}$, and $k$ is the number of unsafe functions that are missed by a threshold, i.e., $k := \sum_{(x, u) \in T_{\text{cal}}} \mathbb{I}(1 - \bar{\delta}(x, 0) < \tau)$. Intuitively, the interval $[\bar{\tau}, \infty)$ contains the most unsafe scores $1 - \bar{\delta}(x, 0)$ for $x \in T_{\text{cal}}$. If a binary analyzer wants to have 90% recall on unsafe functions, $\varepsilon$ is set by $0.1$; if the analyzer wants this desired recall level to be strictly satisfied, $\delta$ needs to be small, where we use $\delta = 10^{-3}$. See Algorithm 1 in Appendix C.

**Theory.** The threshold $\bar{\tau}$ of (2) guarantees a desired recall on unsafe functions over a target unsafe function distribution $\bar{Q}$; see Appendix D for a proof.

**Theorem 1.** Let $\bar{\tau}$ be the solution of (2). For any $\delta$, we have

$$\mathbb{P}_{(x, u) \sim \bar{Q}} [1 - \bar{\delta}(x, 0) \geq \bar{\tau} \mid u \neq \emptyset] \geq 1 - \varepsilon$$

with probability at least $1 - \delta$.

Note that this guarantee on recall is not over a target buggy function distribution $\bar{Q}$; see limitations in Section 7 for details.

5.2 Score Function

In this section, we describe the unsafe score function $\bar{\delta}$ and its learning procedure based on multi-label classification. In particular, we consider three steps in learning the unsafe score function: (1) learning an assembly code embedding function, (2) learning a classification head, and (3) fine-tuning on target.

**Assembly code embedding.** For assembly code embedding learning, we follow the standard procedure in training a language model via transformers [86] because our representation of a function $x$ is assembly code in text. Here, we use RoBERTa-large [53] as our embedding network architecture along with an associated tokenizer.

**Classification head.** After learning the code embedding, we add the fully connected classification head to classify 14 unsafe function categories along with one safe category and minimize the binary-cross-entropy loss on the entire network and source training set $\bar{S}_{\text{train}}$. We denote an unsafe score function trained up to this stage as $\bar{\delta}_{\text{CrateU}}$, and if the threshold is obtained from $\bar{S}_{\text{val}}$, we denote the unsafe classifier by $\hat{u}_{\text{CrateU}}$.

**Fine-tuning on target.** Given a target training set $\bar{T}_{\text{train}}$, the unsafe score function can be further adapted to the target; we fine-tune the unsafe classifier with the same loss on $\bar{T}_{\text{train}}$. We denote this adapted unsafe score function by $\bar{\delta}_{\text{RustSecU}}$, and the threshold is obtained from $\bar{T}_{\text{val}}$, we denote the unsafe classifier by $\hat{u}_{\text{RustSecU}}$.

6.1 Setup

**Datasets.** We consider the Crate and RustSec dataset proposed in Section 4. The CrateU and RustSecU are used for learning classifiers and the RustSecB is used for evaluation. In particular, we randomly split Crate dataset into $\bar{S}_{\text{train}}$, $\bar{S}_{\text{val}}$, and $\bar{S}_{\text{test}}$, where the validation and test splits contain 3,006,862 and 3,175,212 number of functions, respectively, and the training split contains the rest. Similarly, we randomly split Rustsec dataset into $(\bar{T}_{\text{train}}, \bar{T}_{\text{val}}, \bar{T}_{\text{test}})$, where the validation and test splits contain 119,739 and 218,155 number of functions, respectively, and the training split contains the rest. Here, each function in the RustSec dataset has two different labels: one for the unsafe label and another for the bug label. When we use the bug labels for evaluation, we denote the test split by $\bar{T}_{\text{test}}$. Note that in splitting the RustSec dataset, we take 25% of the total functions as train and 25% as validation sets, considering that it is expensive to collect enough data from the RustSec dataset. Importantly, we split data by Rust package names for the Crate dataset and by RustSec ID for the Rustsec dataset for the practical usage of our classifier (i.e., the entire function from a binary is given for analysis).

**Baselines.** We consider three baselines for unsafe classification. One is a random baseline; it randomly chooses its safe score $\bar{\delta}(x, 0)$ for its unsafe classifier $\hat{u}_{\text{rand}}$. The second baseline is an external-call baseline $\hat{u}_{\text{ext}}$: given a function $x$ in binary, it returns 1 if the function instructions contain an external function call, and 0 otherwise. The last baseline is an oracle baseline $\hat{u}_{\text{oracle}}$; this classifier exactly knows whether a function is unsafe or not, thus, providing the performance upper bound of any unsafe classifiers. Note that the same PAC thresholding is used when necessary.

**Metric.** We use two evaluation metrics: the precision-recall curve for the unsafe classification, and the coverage-recall curve for the bug classification. By choosing a threshold via Section 5.1, one point in the coverage-recall curve is chosen...
for the final evaluation. In particular, the precision, recall, and coverage of the unsafe classifier are computed as follows:

\[
\text{precision} := \frac{\sum_{(x,u) \in A_{test}} \mathbb{I}(u = 1 \text{ and } \hat{u}(x) = 1)}{\sum_{(x,u) \in A_{test}} \mathbb{I}(\hat{u}(x) = 1)},
\]

\[
\text{recall} := \frac{\sum_{(x,u) \in A_{test}} \mathbb{I}(u = 1 \text{ and } \hat{u}(x) = 1)}{\sum_{(x,u) \in A_{test}} \mathbb{I}(u = 1)}
\]

\[
\text{coverage} := \frac{\sum_{(x,y) \in T_{test}} S(x) \mathbb{I}(\hat{u}(x) = 1)}{\sum_{(x,y) \in T_{test}} S(x)}
\]

where \( A_{test} \) is \( S_{test} \), \( T_{test} \), or \( T_{test} \). Here, \( S \) is a function size metric in Section 3.1, which counts the number of instructions in a function, including all instructions in its callees.

### 6.2 Crate Dataset

The unsafe classifier of rustspot is evaluated over CrateU and RustSecU. Figure 6(a) shows the precision-recall curve on CrateU for each unsafe type using \( \hat{u}_{\text{CrateU}} \). In particular, the area under the precision-recall curve (AUPRC) of an unsafe classifier is 80.36%, demonstrating that unsafe blocks in the Rust binary are identifiable. Moreover, the AUPRC of the unsafe classifier regarding the external unsafe function call type, \( \text{i.e., CallToUnsafeFunction (external)} \), is 40.64%, which mostly contributes to the AUPRC of unsafe labels.

The unsafe classifier \( \hat{u}_{\text{CrateU}} \) is adapted to RustSecU for the adapted classifier \( \hat{u}_{\text{RustSecU}} \); the AUPRC of the adapted classifier \( \hat{u}_{\text{RustSecU}} \) on RustSecU is 61.82%, while that of \( \hat{u}_{\text{CrateU}} \) before the adaptation is 38.20%, demonstrating that the adaptation is effective; see Figure 9 for the details.

### 6.3 RustSec Dataset

The unsafe classifier is evaluated over RustSecB. Figure 6(b) represents the coverage-recall curve of baselines, including the proposed classifier.

**Random baseline.** The coverage of the random baseline is increased at the same rate as the recall increasing rate; this is equivalent for an analysis tool to randomly choose a function for analysis.

**External-call baseline.** The external-call baseline has low coverage up to the recall of 0.45, but after that, the coverage is dramatically increased as recall increases, since there are many unsafe functions without external function calls.

**Oracle baseline.** The coverage-recall curve by the oracle baseline shows the best possible performance.

**Proposed classifier.** The proposed classifier maintains low coverage for the most recall range. Interestingly, the coverage of the proposed unsafe classifier \( \hat{u}_{\text{RustSecU}} \) is close to the oracle baseline up to 0.8, demonstrating its efficacy.

**PAC thresholding.** The coverage-recall curve shows the trend of coverage and recall with a varying threshold \( \tau \); however, this threshold should be chosen in practice. We use the proposed thresholding algorithm in (2) for \( \tau \), and Figure 6(c) shows the coverage and recall with the chosen threshold in square markers. In particular, when the desired recall of unsafe functions is 90% \( \text{i.e., } \varepsilon = 0.1 \), its empirical recall of buggy functions is close to 90%, which means the desired recall over unsafe-labeled functions can approximately control the recall over bug-labeled functions.

**Qualitative results.** Listing 2 shows a true-positive case. This function \( x \) embeds a memory-safety bug \( \text{i.e., } y = 1 \) and has an unsafe label whose type is \text{DerefOfRawPointer}. The unsafe classifier correctly classifies an unsafe function \( \text{i.e., } \hat{u}(x) = 1 \), which contains a bug, mainly because the classifier recognizes the pattern on dereferencing raw pointers. See Appendix G for additional qualitative results.

### 6.4 White-box Fuzzing Experiments

We applied the proposed unsafe classifier \( \hat{u}_{\text{CrateU}} \) along with libfuzzer and cargo fuzz to show its application in an ideal white-box fuzzing setup, assuming this result provides the best possible performance gain for binary-only fuzzing. cargo fuzz [79] is an open source plugin for Rust ecosystem that enables developers to apply fuzzing on their Rust crates. It uses libfuzzer [64] as a backend by default, and developers can create the fuzzing harness by themselves to test the package. Besides, libfuzzer supports guided fuzzing by providing focus functions and the fuzzer will give more weight on the corpus that touches focused functions. We download the Rust crates by their popularity\(^7\), filter the crates that support cargo fuzz, and get 118 crates with 277 fuzzing targets.

We first launch these targets as normal fuzzing for at most 8 hours and count the number of errors found by the fuzzer. For each target, we launch the fuzzer with default process on our server with AMD EPYC 7452 Processors and wait until the fuzzer reports an error or the process timeout. Then, we build the target crates into binaries in release mode (without fuzzing instrumentation and source code information) and feed these binaries into our unsafe classifier. Then, it proposes a list of functions that are likely unsafe, and we use these functions as our focused functions during fuzzing and relaunch the fuzzers using the same setup for another 8 hours. Importantly, for some binaries, the unsafe classifier has an empty list, which means the classifier considers that the binary is "safe". Then, we just skipped these binaries for the fuzzing process, which provides the time reduction. Our evaluation shows that with the help of our model, a fuzzer can save 20.5% of time by skipping 50 binaries out of 277 and still finding 97.62% \( (41/42^2) \) of the errors. The detailed number of bugs and time saved are shown in the Table 3. We further collect the code coverage of the fuzzing process by utilizing LLVM’s source-based code coverage [65] and count the number of times that unsafe

\(^7\)We use the cumulative download statistics on 14th June 2022

\(^8\)Specifically, we found 27/28 crashes, 3/4 stack/heap overflows, 6/6 out of memory and 5/4 execution timeout errors compared with baseline.
regions are being executed. Because for some targets, the fuzzing process triggers lots of unsafe regions, we normalize the count by $\frac{\text{rustspot hit counts}}{\text{baseline hit counts}+1}$. Then we calculate the sum for all normalized counts, resulting 744.61 out of 227 targets being fuzzed by rustspot, meaning that ours contributes to pass unsafe regions three-time more.

| found errors | baseline | rustspot (ours) |
|--------------|----------|-----------------|
|              |          |                 |
| running time (days) | 79.88 | 63.50 |
| normalized hits of unsafe regions | 744.61 | |

Table 3: Fuzzing Result comparison against baseline. rustspot can help developers save at most 20.5% of the time but still finding 97.6% of the errors in binaries.

Table 4: Performance on various Rust binaries, measured via precision, recall, and AUPRC, where higher is better. Our unsafe classifier achieves high precision, recalling the half of unsafe functions.

6.5 Case Study

We evaluate our unsafe classifier over real world applications to show its generality. In particular, we choose three types of binaries: servo for a web browser, artichoke for a Ruby interpreter, deno for a JavaScript and TypeScript runtime\(^\text{5}\), where these binaries are not in our dataset, while related packages might be included (e.g., smallvec for servo). Different to our evaluation on RustSec datasets, we do not have additional binaries for adaptation, thus we use our unsafe classifier trained and calibrated over CrateU, i.e., $\hat{u}_{\text{CrateU}}$.

Results. Table 4 shows the evaluation results in precision, recall, and AUPRC; overall, our classifier has good result on AUPRC. Besides, the predicted list on unsafe functions by our classifier is quite precise, while recalling about the half of unsafe functions, demonstrating the efficacy even without adaptation, though we believe adaptation on a similar type of binaries would improve the performance. Importantly, PAC thresholding guarantees at least $1 - \epsilon = 90\%$ recall on CrateU, but it does not hold per binary, which is related to performance mismatch due to covariate shift [57].

7 Discussion

Larger unsafe blocks or smaller unsafe blocks. We have demonstrated that detecting unsafe blocks in binaries helps to find a desired number of memory-safety bugs while only covering a small number of instructions. However, this benefit assumes that unsafe code takes a tiny portion of the entire binary by the programmer’s convention on writing smaller unsafe code. If this convention is not met, finding memory-safety bugs in Rust is as difficult as in other unsafe languages, while sacrificing a memory-safety guarantee by safe Rust. Then it is questionable how to balance between a benefit from safe Rust due to smaller unsafe code and a benefit from avoiding reverse engineering due to larger unsafe code.

---

\(^{5}\)We use servo with commit 08bc2d5, artichoke with commit d6a0fa7c7 and deno with v1.23.0.
Rust binary Obfuscation. One possibility to take the benefit of safe Rust is to obfuscate unsafe blocks in Rust binaries to avoid the unsafe classifier. This obfuscation leverages the fact that the data-driven classifiers are fragile to distribution shift [73, 78]. In the bug-finding literature (e.g., fuzzing), obfuscation is not a new idea. For example, Fuzzification [48] introduces an anti-fuzzing technique to protect binaries from state-of-the-art fuzzer techniques. Similarly, anti-unsafe classification can be considered.

Limitations. Rust provides powerful tools like procedural macros to create user-defined macros inside a program. However, this powerful macro leads to true negatives in our rustspot. Because the DWARF debugging information captures source code information before the compiler’s preprocessing steps, it fails to map unsafe blocks inside a macro into binary instructions. Due to the complexity of the workflow of procedural macros, we leave this as future work. For the usability of rustspot, finding a threshold for the unsafe classifier is crucial if an analysis tool wants to control a desired recall on buggy functions. However, without bug-labels (as in our setup), choosing the threshold that satisfies the desired recall rate is infeasible in general. In particular, the guarantee for recall in Theorem 1 is not over the target buggy function distribution $Q$; thus, this guarantee does not eventually lead to the guarantee for recall over bug labels in Equation 1. Instead, we empirically show that $\hat{r}$ nearly satisfies Equation 1.

8 Related work

Unsafe Rust and Its Usage. Although software engineers try to avoid unsafe regions in their program to avoid potential memory safety issues [22], many Rust crates are using “unsafe” more frequently and lead to the implicit usage and wide spread of unsafe blocks in Rust binaries [21]. Besides, studies [68, 5] shows that these usages of unsafe are usually for good or unavoidable reasons, which are not easy to be removed. While unsafe catches programmers’ attention on memory safety, it can be used for reverse engineers to find the weakness of the given Rust binaries as well. To our knowledge, rustspot is the first tool to recover the unsafe regions from raw binary instructions.

Binary Bug Hunting. Approaches to find bugs or vulnerabilities through binary analyses have been proposed [75, 14, 10, 77, 15, 88, 92, 93]. Angr [75] is a powerful framework combining both static and dynamic analyses to automatically find general vulnerabilities in binary executables. In contrast, other tools are tailored to find specific bugs in binaries; oot [88] is designed for spectre attacks, KEPLER [92] is targeted for control-flow hijacking, and DTaint [10] aims to detect taint-style vulnerabilities. Additionally, machine learning has been applied to program analyses for bug finding [58, 52, 63]. VulDeePecker is a system that leverages deep learning to automatically detect bugs inside programs. However, [98] also proposed several open questions that may interfere with the performance of applying machine learning or deep learning to bug hunting. The previous tools and frameworks are designed to find actual bugs inside the binaries, but they require significant resources to scan the whole binary and can only find bugs under specific assumptions. Our rustspot can complement existing tools as a preprocessing tool to largely scale down the search space for Rust binaries.

General Binary Analysis. Beyond bug hunting, general binary analysis is an essential task in computer security, including the following problems: binary-binary code matching, binary-source code matching, function prototype inference, function boundary detection, and malware classification. Some of this research (e.g., function boundary detection) can be regarded as a basis of rustspot. In binary-binary code matching, a function or an entire program in binary is represented in a vector to retrieve functions or programs similar to a given target binary [18, 95, 61]. The core of known approaches is learning binary code representation to summarize the instructions of a function or a program into a vector based on recurrent neural networks [45], graph neural networks [71], or transformer-based models [86]. Similarly, binary-source code matching finds similar binary or source code given source or binary code [96]. Function prototype inference is predicting a function type (e.g., the number of arguments and the type of argument) given instructions of a function [11]. Function boundary detection enumerates the list of the start and end of a function in a binary [42, 74, 50, 17], and malware classification classifies each binary whether it embeds malware or not [69]. Compared to known binary analysis problems, we consider detecting unsafe regions in Rust binaries, while enjoying ideas on binary code representation learning. See additional related work in Appendix A.

9 Conclusion

We claim that Rust unsafe code can be abused via binary reverse engineering to find memory-safety bugs; they can exploit a small amount of unsafe code as a clear spot for memory-safety bugs. To justify our claim, we propose a tool rustspot to collect unsafe labeled functions and learn an unsafe classifier that returns a list of functions to be analyzed. We empirically show that to find 92.92% of memory-safety bugs, only 16.79% of function instructions needs to be analyzed, where the code coverage is at least four times smaller than baselines. As an application, we applied our tool within targeted fuzzing, showing the reduction of fuzzing time.

Ethics consideration. We automatically collect Rust packages from crates.io and manually collect bug information from RustSec reports [27]. All collected data is publicly available, and we do not use the identity of the package as part of rustspot. We evaluate rustspot over known bugs reported in RustSec [27]; thus, we do not disclose new vulnerabilities.
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A Additional Related Work

Debugging information. DWARF [20] is a widely used format for debugging information in ELF programs. We exploit the DWARF debugging information generated by the compiler to automatically generate our labels for learning. Several frameworks have attempted to validate its correctness on optimized code [51, 1, 13, 90] and recover optimized information [47, 91, 39]. This research has been applied in mainstream compilers like gcc, clang, and rustc.

Binary debloating. Debloating is a powerful way to accurately identify and remove unneeded code to avoid potential security risks. State-of-the-art approaches focus on applying feature subsetting, deep learning, and binary analysis to detect the unused features and decrease binary file size [2, 66, 67, 3, 41, 72]. For example, TRIMMER [72] leverages user-provided configuration data to largely reduce binary file size. Slimium [67] uses hybrid program analyses and feature subsetting to achieve binary size reduction on the Chromium web browser. Nevertheless, binary debloating sacrifices several functionalities of a program to achieve the binary size reduction. Instead of finding unused code in binaries, rustspot finds unsafe code in Rust binaries.

B Additional Memory-safety Bug Examples

Producing an invalid value. The following provides additional bug examples in producing an invalid value.

Example 2 (producing an invalid pointer potentially leads to double-free). Listing 3 shows an undefined behavior by producing an invalid intermediate value, leading to double-free. Here, the ownership of p is duplicated after calling function ptr::write and is expected to be consumed by ptr::read. However, if the given function f panics, p will be dropped twice due to the duplication (i.e., double-free). In terms of Definition 1, the programmer assumes that p is a valid pointer after f(ptr::read(p)), but it is violated due to the duplication. Since the program state s goes to unsafe after executing f(ptr::read(p)), we label Line 4 as buggy.

Example 3 (producing an invalid type potentially leads to memory corruption). Listing 4 produces an invalid bool value. In particular, read_scalar_at() converts any byte into type T, including bool. Nevertheless, in Rust, bool can have only two values: 0x00 or 0x01; other values can lead to undefined behaviors in safe Rust code, thus corresponding to memory corruption. If type T is bool and the value in s is invalid, after executing line 6, the program produces an invalid variable x. In terms of Definition 1, we label Line 6 as buggy.

Accessing uninitialized memory. If uninitialized memory is accessed, it potentially exposes sensitive information or leads to memory corruption.

Example 4 (reading from uninitialized memory potentially leads to memory exposure). Listing 5 shows a case on reading from uninitialized memory. Specifically, buf is not initialized (due to set_len()) and passed to the user-provided read implementation. As it is totally valid to read buf within the read(), the uninitialized memory in buf can be exposed. In terms of Definition 1, a programmer may intend to initialize a new buffer after calling set_len() to extend the vector length. However, after executing Line 5, the uninitialized buf is shared via read(), leading to a mismatch between a safe-type of the buffer (i.e., an initialized buffer) and the actual one (i.e., an uninitialized buffer); thus, we mark Line 5 as buggy.

Violating Rust borrowing rules. Rust borrowing rules are strictly enforced by a Rust compiler except for unsafe blocks. Violating the borrowing rules clearly introduces memory-safety bugs, by the definition of the borrowing rules.

Example 5 (violating Rust borrowing rules potentially leads to memory corruption). Listing 6 explains violating Rust

---

Listing 3: Producing an invalid pointer [34] and double-free

```rust
pub fn mutate<T, F: FnOnce(T) -> T> (p: &mut T, f: F) {
    unsafe {
        ptr::write(p, f(ptr::read(p)))
    }
}
```

Listing 4: Producing an invalid bool [28] and memory corruption (where the original code is simplified)

```rust
pub fn read_scalar_at<T: EndianScalar> (s: &[u8], loc: usize) -> T {
    let sz = size_of::<T>();
    let p = (s[loc].loc + sz).as_ptr();
    as *const T;
    let x = unsafe { *p; }
    x.from_little_endian()
}
```

Listing 5: Reading from uninitialized memory [37] and memory exposure

```rust
let mut buf = Vec::with_capacity(data.len());
unsafe {
    buf.set_len(data.len());
}
let bytes = self.read(&mut buf)?;
```

Listing 6: Producing an invalid value

```rust
let x = unsafe { *p; }
x.from_little_endian()
```
Listing 6: violating Rust borrowing rules [30] and memory corruption

```rust
impl<'a, T: 'a> RowMut<'a, T> {
    pub fn raw_slice_mut(&mut self) -> &'a mut [T] {
        unsafe {
            std::slice::from_raw_parts_mut(
                self.row.as_mut_ptr(),
                self.row.cols()()
            )
        }
    }
}
```

boring rules. Here, raw_slice() returns a mutable slice with a different lifetime ('a) from a pointer stored in self (bounded with default 'self lifetime). By calling this function multiple times, a programmer can break Rust’s borrowing rules and create many mutable references, potentially leading to memory corruption or data race. In safe Rust’s design for borrowing rules, there is at most one mutable reference for each memory location. Nevertheless, this intended rule is not guaranteed in Listing 6, leading to a mismatch between a safe-type and the actual type, so we label Line 5-7 as buggy.

C PAC Thresholding Algorithm

Algorithm 1 PAC thresholding algorithm [59, 60]. \( \bar{Z} \) is a set of unsafe functions (e.g., \( \bar{T}_\text{cal} \)).

```text
procedure PS-THRESHOLDING(\( \bar{Z}, \bar{s}, \bar{\varepsilon}, \bar{\delta} \))
\( \bar{\tau} \leftarrow 0 \)
for \( \tau \in \mathbb{R}_{>0} \) do (\( \rightarrow \)) Grid search in ascending order
\( k \leftarrow \sum_{(x,u) \in \bar{Z}} \mathbb{1}(1 - \bar{s}(x,0) < \tau) \)
if \( \theta(k;\bar{Z},\bar{\delta}) \leq \bar{\varepsilon} \) then
\( \bar{\tau} \leftarrow \max(\bar{\tau}, \tau) \)
else
break
return \( \bar{\tau} \)
```

D Proof of Theorem 1

In PAC prediction sets [59, 60], a predictor is represented in a prediction set. We consider how the thresholding classifier is converted to the prediction set to use the PAC prediction set construction algorithm to find our threshold. Recall the unsafe classifier

\[
\hat{u}(x) := \begin{cases} 
1 & \text{if } 1 - \bar{s}(x,0) \geq \tau \\
0 & \text{otherwise}
\end{cases}
\]

Then, we consider the following equivalent prediction set form:

\[
C_{\bar{T}}(x) := \begin{cases} 
1 & \text{if } 1 - \bar{s}(x,0) \geq \tau \\
0 & \text{otherwise}
\end{cases}
\]

From Theorem 1 in [60] and (2), the following holds with probability at least \( 1 - \bar{\varepsilon} \):

\[
P_{(x,u) \in \bar{Z}}[1 \notin C_{\bar{T}}(x) \mid u \neq \{0\}] \leq \bar{\varepsilon}.
\]

Thus, we have

\[
P_{(x,u) \in \bar{Z}}[1 - \bar{s}(x,0) \geq \tau \mid u \neq \{0\}] = P_{(x,u) \in \bar{Z}}[1 \in C_{\bar{T}}(x) \mid u \neq \{0\}] \geq 1 - \bar{\varepsilon},
\]

as claimed.

Figure 7: Crate dataset summary.

E Additional Data Analysis

To illustrate the amount of information in each function, we consider semantic size, which is the ratio of the number of instructions in a function including all callees (i.e., deep size) to the number of instructions in a function without counting callees (i.e., shallow size). As can be seen in Figure 7(a) and Figure 8(a), many functions for both unsafe and safe labels
have larger semantic size, meaning that each function provides a pattern for safe or unsafe label.

Each function can have multiple unsafe labels if the function contains multiple unsafe blocks. The co-occurrence among unsafe labels could be exploited for learning unsafe-embedding functions. Figure 7(b) and Figure 8(b) show the approximate co-occurrence statistics among unsafe labels; in particular, DerefOfRawPointer is frequently used along with an unsafe function call, implying that learning a pattern for unsafe function calls may provide context information to learn a pattern for a dereferencing of a raw pointer.

F Additional Quantitative Results

An additional evaluation over Crate and RustSec datasets is included in Figure 9; the evaluation shows that the adaptation to RustSec improves the unsafe classifier performance on RustSec compared with the classifier without adaptation; see Figure 9 caption for details.
Figure 9: Effect on adaptation to the RustSec dataset. Our unsafe classifier is trained in two stages. In particular, it is first trained over the CrateU training set and evaluated over the CrateU and RustSecU test sets, where the corresponding precision-recall curves are in 9(a) and 9(c) along with the area under the precision-recall curve (AUPRC). Then, this classifier is further adapted to the RustSecU training set and evaluated again over the RustSecU and RustSecU test sets, where the corresponding precision-recall curve and AUPRC are in 9(b) and 9(d), respectively. These evaluations show that the adaptation to the RustSec dataset is effective in detecting more unsafe functions (i.e., the AUPRC on the RustSecU test set is improved to 61.82% from 38.20%).
G Additional Qualitative Results

Listing 7, Listing 8, and Listing 9 include additional qualitative results of the unsafe classifier; see captions for details.

```assembly
1 sub rbp,0x78
2 mov rax, [rsi + 0x38]
3 mov rax, [rsi + 0x40]
4 mov esi, [r8c]
5 call externcall
6 mov qword ptr [rsi - 0x38], rax
7 mov qword ptr [rsi - 0x40], rax
8 mov rax, qword ptr [rsi - 0x50]
9 mov rax, qword ptr [rsi - 0x60]
10 mov rax, qword ptr [rsi - 0x70]
11 mov rsi, qword ptr [rsi - 0x80]
12 call 0x704b740 ; std::str::from_utf8_unchecked
13 |<C>| sub rbp,0x30
14 |<C>| mov qword ptr [rbp + 0x10], rax
15 |<C>| mov qword ptr [rbp + 0x18], rax
16 |<C>| mov qword ptr [rbp + 0x20], rax
17 |<C>| mov qword ptr [rbp + 0x28], rax
18 |<C>| mov qword ptr [rbp + 0x30], rax
19 |<C>| mov qword ptr [rbp + 0x38], rax
20 |<C>| mov qword ptr [rbp + 0x40], rax
21 |<C>| mov qword ptr [rbp + 0x48], rax
22 |<C>| mov qword ptr [rbp + 0x50], rax
23 |<C>| mov qword ptr [rbp + 0x58], rax
24 |<C>| mov qword ptr [rbp + 0x60], rax
25 |<C>| mov qword ptr [rbp + 0x68], rax
26 |<C>| mov qword ptr [rbp + 0x70], rax
27 |<C>| mov qword ptr [rbp + 0x78], rax
28 |<C>| mov qword ptr [rbp + 0x80], rax
29 |<C>| mov qword ptr [rbp + 0x88], rax
30 |<C>| mov qword ptr [rbp + 0x90], rax
31 |<C>| mov qword ptr [rbp + 0x98], rax
32 |<C>| mov qword ptr [rbp + 0xa0], rax
33 |<C>| mov qword ptr [rbp + 0xa8], rax
34 |<C>| mov qword ptr [rbp + 0xb0], rax
35 |<C>| mov qword ptr [rbp + 0xb8], rax
36 |<C>| mov qword ptr [rbp + 0xc0], rax
37 |<C>| mov qword ptr [rbp + 0xc8], rax
38 |<C>| mov qword ptr [rbp + 0xd0], rax
39 |<C>| mov qword ptr [rbp + 0xd8], rax
40 |<C>| mov qword ptr [rbp + 0xe0], rax
41 ret
```

Listing 7: True positive function example. Here, \( y = \{\text{"bug"}\}, \hat{u}(x) = \{\text{"unsafe"}\}, \) “CallToUnsafeFunction” for external calls and internal calls are two unsafe labels associate this function. In particular, this function contains an external function call (i.e., call externcall) and an internal function call (i.e., call 0x704b740, which calls the Rust unsafe function str::from_utf8_unchecked) from the Rust standard library. The from_utf8_unchecked function code is also part of the input of the unsafe classifier with the prefix |<C>|; thus, this can be leveraged by the classifier for the correct classification.

```assembly
1 push rbx
2 sub rsp, 0x18
3 mov rbx, rdi
4 mov rax, qword ptr [rdi]
5 cmp rax, 3
6 jne 0x2f5ca2
7 add rsp, 0x18
8 ret
9 push rax
10 lea rdi, [rip + 0x8f21f]
11 lea rdx, [rip + 0x356be1]
12 lea rax, [rip + 0x338740]
13 lea rdx, [rip + 0x10]
14 mov esi, 1
15 call externcall
16 add rsp, 0x10
17 pop rbx
18 nop word ptr cs:[rax + rax]
19 ret
20 push rax
21 lea rdi, [rip + 0x8f21f]
22 lea rdx, [rip + 0x356be1]
23 lea rax, [rip - 0x26ff6d]
24 mov esi, 0x24
25 call rax
26 ud2
27 nop
```

Listing 8: False positive function x. Here, \( y = \{\text{"no bug"}\}, \hat{u}(x) = \{\text{"unsafe"}\}, \) and \( u = \{\text{"safe"}\} \). This function calls the Rust safe function std::sync::Once::call_once_force, thus the original function x needs not to be unsafe. However, the compiled call_once_force includes an external function call, which is the reason that the unsafe classifier incorrectly classifies this as unsafe.

```assembly
1 push rax
2 lea rdi, [rip + 0x8f21f]
3 lea rdx, [rip + 0x356be1]
4 lea rax, [rip - 0x26ff6d]
5 mov esi, 0x24
6 call rax
7 ud2
8 nop
```

Listing 9: False positive case. Here, \( y = \{\text{"no bug"}\}, \hat{u}(x) = \{\text{"unsafe"}\}, \) and \( u = \{\text{"safe"}\} \). The unsafe classifier may not have enough context to correctly classify this function due to short assembly code and the lack of registry information.