Out of Sight, Out of Place: Detecting and Assessing Swapped Arguments

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Abstract—Programmers often add meaningful information about program semantics when naming program entities such as variables, functions, and macros. However, static analysis tools typically discount this information when they look for bugs in a program. In this work, we describe the design and implementation of a static analysis checker called SWAPD, which uses the natural language information in programs to warn about mistakenly-swapped arguments at call sites. SWAPD combines two independent detection strategies to improve the effectiveness of the overall checker. We present the results of a comprehensive evaluation of SWAPD over a large corpus of C and C++ programs totaling 417 million lines of code. In this evaluation, SWAPD found 154 manually-vetted real-world cases of mistakenly-swapped arguments, suggesting that such errors—while not pervasive in released code—are a real problem and a worthwhile target for static analysis.

Index Terms—static analysis, natural language, swapped arguments, big code

I. INTRODUCTION

Static analysis tools consist of automated “checkers”, each of which identifies potential problems by looking for matches of a known code defect pattern or violations of an established program development rule. However, traditional static analysis techniques—such as those based on data-flow analysis—do not use the rich natural language information in programs: variable names, field names in a structure or a class, function names, macro names, etc. Programmers seldom choose these names at random; they select names that convey information about the semantic concepts they are manipulating, with identifiable patterns in the creation, composition, and usage of those names. As we show in this work, static analysis tools can and should use these patterns to detect more bugs.

In this paper we introduce SWAPD, an automated static analysis checker that uses natural language information to detect mistakenly swapped arguments at call sites. Listing 1 shows an example of such a mistaken swap, found with SWAPD in the open-source code for the editor xvile [1]. Here, the kill function from signal.h is called incorrectly: the arguments for process identifier and signal have been swapped. Because the two arguments are type compatible, even the arguments for process identifier and signal have been swapped. Incorrect argument ordering is an easy mistake to make when programming in a language that supports positional argument\(^*\), especially if the declaration for the callee function is not readily available. Programmer confusion may be exacerbated by certain function and interface design choices, such as counter-intuitive argument ordering or long parameter lists. In typed programming languages, type checking may catch some swapped argument errors, but not all, as seen in Listing 1.

Listing 1. Bug found with SWAPD: the arguments on line 5 are mistakenly swapped.

```
if (child < 0 && errno == EINTR) {
  kill(SIGKILL, cpid);
}
```

Listing 2. Bug found by SWAPD in the open-source code for the editor xvile [1].

```
/* ... */
*first_event_return */;
```

We have found that these two detection strategies are most effective when used in combination. In particular, we make use of statistical data to reduce both false positives (§III-F) and false negatives (§III-G). As a motivating example, consider the GPaste [3] bug in Listing 2 also found with SWAPD. Here, the argument names are atypical in their current positions, but common in swapped positions, it may indicate an error.

```
if (XQueryExtension (display, "XInputExtension",
&xinput_opcode, &xinput_error_base,
" Xconst char *
/* first_event_return */;
```

Underpinning SWAPD are two observations about developer behavior when naming program entities. First, programmers often choose argument names that are similar to parameter names, due to an underlying conceptual match between the two [2]. Therefore, as in Listing 1, an accidental swap may have taken place if both (a) argument names do not cover (i.e., have a sufficient correspondence with) their parameter names, and (b) they would cover if argument positions were swapped. Second, if we examine several calls to a function (e.g., calls to a library function in a large code corpus), we find discernible statistical patterns with respect to argument names and their positions in the calls. Statistically, if argument names are atypical in their current positions, but common in swapped positions, it may indicate an error.

```
if (XQueryExtension (display, "XInputExtension",
&xinput_opcode, &xinput_error_base,
" Xconst char *
/* first_event_return */;
```

*)Roger Scott performed this work while at GrammaTech.
†All the bugs listed in this paper were found with SWAPD on real-world code not written by the authors. For the sake of presentation, the listings simplify or elide the code context.

2That is, the position of the arguments in a function call denotes which parameter they correspond to.
no parameter names are available in the declaration, so the second, statistical technique was key to detecting the bug.

A key feature of SwapD is that we split parameter and argument names into smaller units, called morphemes\(^1\) before applying our techniques. Operating on morphemes rather than whole names is one of the factors that distinguishes SwapD from closely related works \([4], [5]\). Splitting is motivated by the intuition that program identifiers are often constructed by agglutinating two or more morphemes. \(\text{Listing 1}\) and \(\text{Listing 2}\) represent individual examples of this naming behavior. Indeed, \(\text{Figure 5}\) \((\text{§IV-D})\) shows that a significant portion of the corpus uses names containing multiple morphemes. For example, in \(\text{Listing 1}\) a naïve attempt to match parameters and arguments based on string edit distances could fail, but splitting \(\text{SIGKILL}\) into \(\text{sig}\) and \(\text{kill}\), and \(\text{cpid}\) into \(\text{c}\) and \(\text{pid}\) makes the correspondence clear. Our morpheme-based approach also allows us to improve signal by removing morphemes that appear in multiple arguments in a call; those likely represent conceptual information about the calling context rather than about the intended correspondence to parameters. For example, in \(\text{Listing 2}\) splitting \(\text{xinput\_error\_base}\) and \(\text{xinput\_event\_base}\) into constituent morphemes (and eliminating the common morphemes \(\text{xinput}\) and \(\text{base}\)) helps identify the underlying pattern—that \(\text{error}\) and \(\text{event}\) are statistically more likely in their swapped positions. We have found real bugs with multi-morpheme names \((\text{e.g., Listing 6})\), as summarized in \(\text{Figure 6}\) \((\text{§IV-D})\).

The techniques used in SwapD are largely programming language agnostic. They are broadly applicable to programs in languages that support positional arguments. We have implemented a SwapD prototype targeting C/C++ code; those languages are heavily used in security and reliability-critical software, which provides particular motivation for accurate bug detection. During our empirical evaluation and triage of SwapD warnings, we found that many apparent argument swaps are intentional. Thus, we have designed and adapted a variety of techniques to reduce the number of false positives. Our major contributions include:

- A cover-based checker for detecting swapped arguments via mismatches between argument and parameter names.
- A statistical checker for swapped arguments based on data collected from a large code corpus.
- A morpheme-oriented handling of names in both these approaches, for increasing the relevant signal present in names.
- A hybrid approach combining the two checkers and further false positive reduction techniques to achieve high accuracy in detecting swapped-argument errors.
- A comprehensive evaluation of SwapD on 417 million lines of open-source C/C++ code corpus \([6]\); we believe our evaluation to be one of the largest in this research area, especially for C/C++. SwapD found 154 swapped argument errors across this corpus. This figure suggests that, while swapped-argument errors are not extremely common, they are a real problem, and efforts to detect them are likely to provide value to developers.

The remainder of this paper is organized as follows: we give an overview of SwapD \((\text{§II})\); provide details of specific algorithms and techniques \((\text{§III})\); present the results of our empirical evaluation \((\text{§IV})\); discuss related work \((\text{§V})\); and conclude \((\text{§VI})\).

## II. Overview

In this section, we give an overview of SwapD. We include a number of forward references to \(\text{§III}\) that contain further details on relevant algorithms, techniques, and heuristics.

\(\text{Figure 1}\) is an overview of SwapD, featuring the bug in \(\text{Listing 1}\). The top left quadrant shows the input to SwapD: the call site being checked, and the corresponding function declaration. The function declaration is an optional input—if it is not available, then the cover-based checker is skipped. Given a call site, we extract names \((\text{§III-A})\), from the argument expressions at the call site and from the parameters in the callee function declaration (if available). Next, we split \((\text{§III-B})\) both argument and parameter names into morphemes.

Offline, we use a large corpus of code to compute a statistical database \((\text{§III-D})\), shown in the bottom left quadrant of \(\text{Figure 1}\). The database is a key-value store, where keys are triples consisting of a function name, argument position, and morpheme. The values are weights indicating the number of projects in the corpus where the morpheme appears in calls to that function, at that argument position. Informally, the weight reflects the number of human programmer communities who considered that the morpheme is appropriate to use at the given argument position for that function.

The right-hand portion of the diagram shows the SwapD pipeline of four stages. First, we compare the parameter morphemes and argument morphemes in the cover-based checker \((\text{§III-E})\). This stage does not need the statistical database, but it does require the function declaration with parameter names.

If the cover-based checker finds a suspected error, SwapD uses the statistical database to perform further vetting \((\text{§III-F})\) of the warning. The vetting rules out false positives due to usage patterns for certain functions where seemingly-swapped argument orderings are not rare, indicating that they could have a genuine and intentional use case. If we did report such warnings, there could be a lot of false positives due to function-specific patterns adopted by developers. If the suspected error passes the vetting step, we move on to the false-positive filtering stage described further below.

```
1 // declaration in GStreamer
2 guint64 gst_util_uint64_scale (guint64 val,
   guint64 num, guint64 denom);

3 // use in gst-plugins
4 diff = gst_util_uint64_scale_int (diff,
   denom_rate, num_rate);
```

\(\text{Listing 3}\) shows a function declaration from GStreamer \([7]\) and a callsite with a likely intentional swap. It is statistically

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\(^1\)From the linguistic term for a unit of meaning in a natural language.
not rare to call `gst_util_uint64_scale_int` with the morphemes `denomenum` and `num` in the second and third argument positions respectively, i.e., in a swapped order based on parameter names, possibly as a shortcut for computing the reciprocal of the fraction. We discard such warnings.

If the cover-based checker and the statistical vetting do not find any errors at a call site, or are not applicable (as in Listing 2), SWAPD runs the statistical checker (§III-C) to look for other evidence of potential errors using data from the statistical database. Intuitively, we look for pairs of morphemes that appear at two argument positions at the call site, with the property that, statistically, each morpheme is significantly more common at the other’s position than at its own. Hypothetically, suppose the cover-based checker was not able to identify the error shown in Figure 1. The statistical checker gives SWAPD another chance to catch the error: the statistical database suggests that the `pid` morpheme is often used in the first position at a `kill` call site, and the `sig` morpheme is often used in the second position. This statistical data suggests that the morphemes at this call site may have been swapped. Note that both the cover-based checker and the statistical checker could have identified the same error: the statistical database suggests that the `pid` morpheme is often used in the first position at a `kill` call site, and the `sig` morpheme is often used in the second position. This statistical data suggests that the morphemes at this call site may have been swapped. Note that both the cover-based checker and the statistical checker could have identified the same error: the statistical database suggests that the `pid` morpheme is often used in the first position at a `kill` call site, and the `sig` morpheme is often used in the second position. This statistical data suggests that the morphemes at this call site may have been swapped.

The final stage for all candidate warnings is false-positive filtering (§III-H). It applies various heuristics to distinguish between intentional and mistaken swaps. For example, consider Listing 4 which presents a false-positive finding in GrafX2 [8], filtered out by SWAPD. The second call to `iconv_open` at line 6 uses argument names that appear to be swapped; however, there is a call to the same function with the arguments in the canonical order on the preceding line. If the programmer calls the function “both ways”, with calls in close proximity to each other, it is likely that both usages are deliberate (because it undermines the theory that the swap was due to not knowing the correct order). We use several false-positive filtering heuristics, including one motivated by the call pattern in Listing 4.

```
1 // declaration in iconv.h
2 iconv_t iconv_open(const char *tocode, const char *
3 fromcode);
4 // use in grafx2
5 cd = iconv_open(TOCODE, FROMCODE); // From UTF8
6 to ANSI
7 cd_inv = iconv_open(FROMCODE, TOCODE); // From
8 ANSI to UTF8

Listing 4. The candidate warning on line 6 is ruled out in the false-
9 positive filtering stage because of the nearby correct call on line 5.
```

Throughout our pipeline, we use techniques to minimize noise and maximize signal in the natural language information. One such technique is comparing morphemes to each other using a similarity metric that takes into account abbreviations (§III-C): for example, `msg` is a common abbreviation for `message`. Another technique is to remove morphemes that are common to pairs of argument names being checked, such as `remote` in Listing 5. Removal of the common morpheme allows SWAPD to detect this bug in BoNeSi [9].

```
1 // declaration in libnet
2 libnet_ptag_t libnet_build_tcp(uint16_t sp, uint16_t dp,
3 uint16_t seq, uint16_t ack, /*
4 9 more parameters ... */);
```
A. Extracting name information

SwAppD begins by extracting names from argument expressions at call sites. If the corresponding declarations are available and include parameter names, those names are also extracted. We modeled our name extraction on DeepBugs [5], with adaptations to C and C++. For an abstract syntax tree extracted. We modeled our name extraction on DeepBugs [5], available and include parameter names, those names are also expressions at call sites. If the corresponding declarations are checked, and parameter names for function declarations.

In summary, SwAppD uses a hybrid approach based on both non-statistical and statistical techniques to detect and confirm swapped-argument errors.

III. Design and Implementation

This section provides details about specific stages, algorithms, and heuristics of SwAppD.

A. Extracting name information

SwAppD begins by extracting names from argument expressions at call sites. If the corresponding declarations are available and include parameter names, those names are also extracted. We modeled our name extraction on DeepBugs [5], with adaptations to C and C++. For an abstract syntax tree extracted. We modeled our name extraction on DeepBugs [5], available and include parameter names, those names are also expressions at call sites. If the corresponding declarations are checked, and parameter names for function declarations.

To handle C/C++ macros, we use information from the preprocessor input rather than the parser input (which is the preprocessor output), which often allows us to operate on more meaningful symbolic names. If an entire function call is a result of a macro expansion, or if it is a virtual function call, we skip collecting names from that call site.

B. Splitting names into morphemes

We split argument names for the input call site to be checked, and parameter names for function declarations. We also split argument names when building the statistical database (III-D). Our prototype uses the Ronin [10] identifier-splitting algorithm. Ronin is an extension of the Samurai [11] algorithm, and uses a global table of token frequencies. Additionally, during splitting, we drop very common morphemes like “get”, “set”, “i”, “j”, etc.

C. Morpheme similarity metric

Computing the similarity between two morphemes is a fundamental operation in SwAppD. We define a similarity metric \( \sim \) to quantify the degree of correspondence between two morphemes while allowing for abbreviations. If two morphemes do not have the same first character, their \( \sim \) value is zero. Otherwise, their \( \sim \) value is computed by applying a penalty for each character that must be deleted from a morpheme in order for the resulting strings to contain the same characters in the same order. The penalty is lower for vowels than for consonants, decreases toward the end of the string, and is zero for a final “s” (to account for singular/plural forms). Our penalty for missing characters is normalized by the length of the morphemes, so in longer morphemes we allow for more missing characters while still maintaining a high similarity. We say two morphemes are sufficiently similar for a particular purpose if the value of \( \sim \) is greater than a context-specific threshold. Note that \( \sim \) can be naturally extended to be aware of synonyms; the end of [IV-D] presents a brief discussion of such an experimental extension.

D. Computing a statistical database

The statistical database is keyed by triples consisting of a function name \( f \), an argument position \( i \), and a morpheme \( m \). For each such triple, it contains a weight \( w(f, m, i) \). The weight captures the number of projects in the corpus where morpheme \( m \) appears at position \( i \) in a call site for \( f \).

For a given function \( f \), morpheme \( m \), and argument positions \( i \) and \( j \), we can use the weights in the database to compute a numerical relative frequency score:

\[
\psi(f, m, i, j) = \frac{w(f, m, i)}{w(f, m, j)}
\]

This score attempts to quantify how much more common the morpheme \( m \) is at argument position \( i \) than at argument position \( j \) at call sites to \( f \). In the remainder of the paper, we will sometimes use the notation \( \psi(m, i, j) \), omitting the function \( f \) when it is clear from context. When we build the database, we use the splitting techniques described in [III-B] and we eliminate common morphemes that appear in all argument positions at a call site.

E. Cover-based checker

The cover-based checker detects swapped-argument errors if the morphemes in the argument names better “cover” the morphemes in the parameter names when argument positions are swapped at a call site. This checker is skipped if a function declaration lacks parameter names.

After splitting the parameter and argument names into morphemes, we proceed pairwise, for each pair of argument positions \( i \) and \( j \). In the rest of this paper, \( A_i \) and \( A_j \) denote the sets of argument morphemes at positions \( i \) and \( j \) respectively; \( P_i \) and \( P_j \) denote the sets of parameter morphemes at corresponding positions.

First, we eliminate any morphemes common to \( A_i \) and \( A_j \), and similarly for \( P_i \) and \( P_j \), to handle cases like Listing 5.
If this elimination leaves any of $A_i, A_j, P_i$, or $P_j$ empty, the cover checker does not proceed any further.

Next, we compute the quality of the match, or “cover”, from a set of argument morphemes to a set of parameter morphemes. We run this computation for the original order, computing how well $A_i$ covers $P_i$ and $A_j$ covers $P_j$, and for the “swapped” order, i.e., how well $A_i$ covers $P_j$ and $A_j$ covers $P_i$.

Informally, a set of argument morphemes cover a set of parameter morphemes if every parameter morpheme is sufficiently similar to (using the metric $\sim$ described in (III-C)) at least one argument morpheme. This relation is asymmetric: it is possible to have argument morphemes that are not similar to any parameter morpheme, yet still have coverage. However, if a parameter morpheme is not similar to any argument morpheme, then there is no coverage.

We formalize a notion of coverage $C(A, P)$ for an argument morpheme set $A$ and a parameter morpheme set $P$:

$$C(A, P) = \min_{p \in P} \max_{a \in A} (a \sim p)$$

Our criterion for reporting a swapped-argument warning is based on two thresholds, $\alpha_1$ and $\alpha_2$, empirically determined to be 0.5 and 0.75 respectively. We produce a candidate warning if and only if both of the following hold:

$$(C(A_i, P_j) < \alpha_1) \land (C(A_j, P_i) < \alpha_1)$$

$$(C(A_i, P_j) > \alpha_2) \land (C(A_j, P_i) > \alpha_2)$$

Informally, we require both sufficiently bad coverage in the current positions and sufficiently good coverage in the swapped positions.

Listing 6 shows an example bug found using the cover-based checker. Figure 2 depicts the strong coverage mapping when arguments at position 3 and 4 are swapped.

### F. Statistical vetting

We perform statistical vetting when the cover-based checker flags a pair of arguments in positions $i$ and $j$ at a call site as potentially swapped. We compute $\max_{m \in A_i} \psi(m, i, j)$ and $\max_{m \in A_j} \psi(m, j, i)$. If either of these quantities exceeds a vetting threshold $\beta$ (empirically determined to be 1), we conclude that the usage in question is statistically not rare and so do not report a warning. Listing 3 shows such a case.

We evaluated the results for a variety of settings and choose the best precision/yield trade-off in our judgment. The space constraints prevent us from providing further details of this process for each threshold.

### G. Statistical checks

When the cover-based checker does not find a warning at a call site, we run the statistical checker. It uses the statistical database (III-D) and the argument names at the call site. The statistical checker can run even when the callee declaration does not include parameter names or cannot be retrieved.

If the statistical database does not include statistics for the function called at a call site, the statistical checker is skipped. Otherwise, it considers every possible pair of argument positions $i$ and $j$, and detects instances where two morphemes are likely swapped across those positions using the following approach. As before, we eliminate common morphemes between $A_i$ and $A_j$. After such elimination, if either $A_i$ or $A_j$ are empty, we skip the rest of the steps below for $i$ and $j$.

We now look for pairs of argument morphemes $a_i \in A_i$ and $a_j \in A_j$ such that $\min(\psi(a_i, j, i), \psi(a_j, i, j)) > \gamma$, for a threshold $\gamma$ (empirically selected to be 5). Informally, we look at how much more common each morpheme is in the other’s position than in its own, and require the lesser of those two “misplacement” scores to be greater than $\gamma$.

We also require that $A_i \setminus a_i = A_j \setminus a_j$, i.e., exactly one morpheme is swapped from the two morpheme sets $A_i$ and $A_j$. If we find such a pair of morphemes $a_i$ and $a_j$, we perform one more check. We find the morpheme $m$ with the biggest statistical difference in frequency between position $j$ and position $i$, i.e., $m = \arg\max_x |w(f, x, j) - w(f, x, i)|$. We verify that $a_i$ is sufficiently similar to $m$. The intuition is that if morpheme $a_i$ is common in both positions $i$ and $j$, then the likelihood of a swap is lower; we are looking for evidence that moving $a_i$ from $i$ to $j$ would bring the situation closer to what is statistically most common. We perform a symmetric check for $a_j$. If both checks pass, we produce a candidate swapped-argument warning involving argument positions $i$ and $j$ and proceed with further false-positive reduction. Note that the requirements and checks in this paragraph could be relaxed to potentially catch more bugs, however, at the expense of increased false positive rates.

### H. False-positive filtering

Weeding out intentionally- vs. mistakenly-swapped arguments can be difficult. We have developed a collection of heuristics to identify likely intentional swaps. Some of them
come from the literature; we developed others empirically by manually examining SWAPD warnings, identifying false positives, and formalizing common features of those false positives. Without false-positive filtering of this nature, the developer experience of using such checkers can be frustrating. We list our major heuristics below.

**White-list words.** Some words hint that a swap might be intentional, e.g., “swap”, “exchange”, “rotate”, or “flip”. We expand on the “nested in reverse” heuristic [4], and look for such words in the following locations: the name of the callee function, the name of the caller function, nearby conditional expressions (i.e., the last five branches along the current execution path, see [Listing 4] from Mate Panel Libs [12]), the six immediately-preceding lines of source code (including any comment contents). We consider presence of such words to be indicative of false positives, and filter out such warnings.

```c
1 // decl in gdk-pixbuf.h
2 GdkPixbuf* gdk_pixbuf_new /* 3 params */ int
3   width, int height);
4 // use in mate-panel-libs
5 if (background->rotate_image /* & */ ...)
6   // .. several lines of code, and nested if
7   x = gdk_pixbuf_new /* 3 args */ int, height, width);
Listing 7. False-positive warning filtered out, because “rotate” is in a nearby conditional expression.
```

**Swap distance.** We found that on real-world code, all warnings for argument positions $i$ and $j$ with $|i - j| > 2$ were false positives. Therefore, we do not report such warnings.

**Geometric code patterns.** In geometric code, it is common to combine swapping of axes with negation of one of two values to achieve various transformations. We exclude as intentional any apparent swapped-argument calls that negate exactly one of the two arguments involved.

**Type checking.** We eliminate some false positives through simple type checking on the types of the two arguments involved (similar to [2], [13]). The intuition is that a swap of arguments with incompatible types would have been detected in development via a compiler error. Even among compatible types, if the swapped order requires more type coercion, that may argue for the correctness of the existing code.

**Nearby declaration.** If the declaration of the callee function is in the same source file as the call site, we consider the warning a false positive. This heuristic is based on our empirical findings, and on the intuition that erroneous swaps happen when the programmer forgets the correct argument order. If the declaration is nearby, the programmer likely is aware of the correct argument order.

**Nearby correct call.** If there are other calls to the same function, but with unswapped arguments, within the same caller function (see Listing 4), we consider the warning a false positive. This heuristic (similar to the “duplicate method calls” heuristic [4]) is based on empirical findings, and on an intuition about reminder proximity similar to that of the previous heuristic.

**Swap is not rare.** If the suspected swap is not an isolated event, but occurs in three or more separate callsites within the same calling function, we consider it a false positive. Our observation is that anomalies tend to be intentional unless they occur very rarely. This heuristic causes us not to report cases where a function is called at several callsites consistently with the wrong argument order; however, true positives of this kind are far outweighed by false positives.

### IV. Evaluation

In this section, we present the results of an empirical evaluation of SWAPD on a large C and C++ code corpus. The major research questions we consider are:

- **R1.** How well does SWAPD find warnings in real-world open-source code?
- **R2.** What is the value-add of the different stages in SWAPD?
- **R3.** (a) How often are argument and parameter names constructed from multiple morphemes? (b) How many of the true positives found involve multiple morphemes? These questions are aimed at seeking justification for morpheme-level reasoning, instead of operating directly on whole names.
- **R4.** (a) What effect does the corpus size used for the statistical database have on SWAPD’s findings? (b) What is the effect of leaving out those projects from the statistical database, on which SWAPD produces any warnings? We also provide a discussion of the warnings triaged (§IV-F) and threats to validity (§IV-G) of our work.

#### A. Prototype implementation and corpus

We use the commercial static analysis tool CodeSonar [14] to extract name information from call sites and their corresponding declarations, when available. We implemented the statistics database computation (§III-D) and the SWAPD checker prototype in Python. Our prototype generates warnings in the SARIF format [15]. Such warnings can be imported into an IDE or other SARIF viewers (such as CodeSonar) for manual inspection and triage. CodeSonar remembers the triage result (i.e., true/false positive), as well as other user annotations, by fingerprinting the warning location. We found this ability to be helpful for manual construction of ground truth for the evaluation, and during review of the results.

We computed the statistical database using the open-source Fedora 29 source-package repository [6], filtered to include only projects containing C or C++ code. We performed additional filtering to reduce duplication and eliminated extremely large projects. We successfully processed 6541 projects, consisting of about 417 million lines of code. We refer to this set of projects as the SRPM corpus in the rest of this paper. The resulting statistical database contains morpheme information for over four thousand functions.

#### B. Evaluation methodology

We considered evaluating SWAPD on both real-world code and on a synthetically-generated dataset with randomly injected swapped arguments. We decided against the latter, because it is unclear how to generate a synthetic dataset with a realistic distribution of both erroneous and intentional
swaps. In practice, intentional swaps far outnumber actual swap errors, so we do not believe that a naïve injection approach that disregards them would lead to a realistic dataset; thus, evaluation results on synthetic datasets may not carry over to real-world code. Therefore, we decided to conduct an evaluation exclusively on real-world open-source code. We perform our evaluation on the SRPM corpus, i.e., 417 million lines of C and C++ code. As far as we are aware, our evaluation is the largest (in terms of number of lines of code) for a swapped-argument checker on any programming language [4], [5]; and the largest by far [13] on C/C++.

A limitation of using real-world code for evaluation is the lack of pre-existing ground truth. To obtain a list of true- and false-positive warnings, we ran SWAPD under different configurations (described in IV-C) to obtain a total of 4141 unique warnings reported on the SRPM corpus. Of these, we sampled and manually triaged 859 unique warnings: we marked 183 of these as true positives, and 676 as false positives. When SWAPD is run again on the SRPM corpus under any configuration, a warning reported at a triaged location is recognized and automatically classified as a true or a false positive. The manual triage task was shared by six experienced developers, some of whom were involved in the development of SWAPD. We applied a conservative triage strategy—marking warnings as true positives if they reflect issues worth raising in a code review (i.e., real bugs or problems worth fixing even if there is no runtime error). Otherwise, we marked warnings as false positives. Listing 8 from OpenVAS libraries [16] shows an example warning marked as a false positive: we suspect that the swap on line 6 is intentional, because on line 5, the format string “src host %s” uses an argument computed from dst.

```
1 // declaration
2 int init_v6_capture_device (struct in6_addr src, struct in6_addr dst, char *filter);
3 // use in openvas-libraries
4 snprintf (filter, sizeof (filter), "ip6 and src host %s", inet_ntop(AF_INET6, dst, addr, sizeof (addr)));
5 bpff = init_v6_capture_device (*dst, src, filter);
```

Listing 8. Warning triaged as a false positive.

Because we manually triaged a sample of warnings, we use precision and yield as our evaluation metrics. Precision is the ratio of the number of true-positive warnings to the total number of warnings. Yield is the total number of reported true-positive warnings from our ground-truth dataset. Yield is a proxy for recall: since there is no practical way to determine the full set of all swapped-argument errors in the corpus, we cannot determine what percentage of them we have found.

Making SWAPD practically useful requires balancing precision and yield. High precision with low yield leads to few reported warnings; while these warnings are likely to be real problems, many other real problems may be missed. Low precision with high yield is also not ideal, because it leads to large numbers of false positives. The developer effort to sift through those can cause frustration and reduce adoption. In a practical tool, scoring and sorting can be used to balance these conflicting concerns. By assigning scores to warnings based on their likelihood of being true positives, we can show them to the user in a descending order. The user can then decide when the effort of further manual triaging is no longer justified by the likely benefit of discovering an additional true positive. Scoring the warnings from SWAPD is an interesting problem that is outside the scope of this paper.

C. Evaluating various stages

As outlined in Section II, SWAPD involves a multi-stage pipeline, with four stages: (1) cover-based checker, (2) statistical vetting, (3) statistical checker, and (4) false-positive filtering. Each of these stages impact precision and/or yield. To expose the impact of each stage, we evaluated the precision and yield of SWAPD in a variety of different configurations. In each configuration name, the numbers indicate which of the four stages are enabled. For example, in C_3, only stage 3 is enabled, and the rest of the stages are disabled.

Figure 3 shows the precision and yield of SWAPD for various configurations. A few observations are clear: C_{1234} shows the best trade-off between precision and yield. C_{123} has higher yield, but very low precision—it reports an order-of-magnitude more warnings in total than C_{1234}. However, 75% of the warnings from C_{123} are false positives, which justifies our adoption of the false-positive filtering stage to increase precision. In fact, all the configurations without stage 4 enabled (i.e., C_{1}, C_{12}, C_{3}, C_{123}) have low precision.

Configurations other than C_{1234} and C_{123} have much lower yield, suggesting that relying solely on either the cover-based checker or the statistical checker misses several true-positive warnings, justifying our hybrid approach. Comparing C_{12} vs. C_{1}, and C_{14} vs. C_{124}, we see a small increase in precision traded for a small decrease in yield: thus, cross-checking with the statistical database to perform statistical vetting of the cover-based checker warnings can be useful if a user prefers precision over yield.

In summary, these results answer R1: with all the four stages enabled, SWAPD finds 154 true-positive warnings on the SRPM corpus, with a precision of 67%. These results also answer R2: each of the four stages contribute to either increasing precision or increasing yield, justifying the use of each stage. Figure 4 shows the overlap in true-positive warnings between the cover-based checker and the statistical checker—both these approaches largely find different sets of true warnings, further bolstering the case to use both of them.

D. The case for morpheme-level reasoning

As described in §I, operating on morphemes instead of whole names is a key feature of our approach. Finding bugs such as those in Listing 5 and Listing 6 highly benefit from morpheme-level reasoning: using a string-distance metric on whole names is not a good fit for finding such errors. However, \textsuperscript{5}C_{1234} reports 402 warnings in total on the SRPM corpus. Of these, 231 warnings are present in our manually-triaged ground-truth dataset. Among these 231 warnings, 154 are true positives.
if almost all the argument and parameter names provided by
developers consist of single morphemes, then the morpheme-
level reasoning boils down to whole-name-level reasoning,
making morpheme-level reasoning overkill.

**Figure 5** answers R3(a); it shows how often argument names and parameter names in the SRPM corpus are constructed with different morpheme-set sizes. If we cannot extract a name from a call site or a declaration, it does not get counted making morpheme-level reasoning overkill.

Nearly 42% of true-positive warnings involve names with more than one morpheme, confirming that our morpheme-level reasoning in the different stages are likely useful in identifying real bugs.

Inclusion of synonym relationships in the similarity metric \( \sim \) would allow morpheme-level reasoning to find even more errors. For example, if we consider `size` and `count` as synonyms, i.e., \( \sim (\text{size}, \text{count}) = 1 \), then SWAPD finds the error shown in **Listing 9** from Guile [17]. As future work, we want to automatically extract synonyms from code corpora, and extend our morpheme-similarity metric with knowledge of these synonyms.

**E. Effect of corpus used for computing the statistical database**

In **Figure 7**, we take different randomly-chosen subsets (1%, 5%, 25%) of the SRPM corpus to compute the statistical database, and present the results of running C_{1234} on the SRPM corpus with these different statistical databases. Each random subset is computed five times. This plot serves to answer R3(a), showing the effect of the corpus size used for the statistical database on SWAPD’s findings. All the five random trials with 1% of the corpus, and most of the five random trials with 5% of the corpus, are in the bottom-left quadrant (low precision and low yield). However, all the rest of random

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**Fig. 3.** Precision vs. yield for various SWAPD configurations. C_{1234} has the best trade-off between precision and yield.

**Fig. 4.** Presents the number of unique true-positive warnings reported by cover-based checker (C_{1}) only, statistical checker (C_{3}) only, and by both.

**Fig. 5.** Frequency distribution of morpheme-set sizes for argument names (left) and parameter names (right) across the SRPM corpus. The y-axis in both the charts (note different scales) indicates frequency; the x-axis provides morpheme-set size.

**Fig. 6.** Maximum number of morphemes (argument or parameter morphemes in either positions) involved in a reported true positive by C_{1234}.

**Fig. 7.** Precision vs. yield for various C_{D} configurations. The best trade-off between precision and yield.
subsets are in the top-right quadrant (high precision and high yield), suggesting that statistical database computation from relatively small subsets of the SRPM corpus (i.e., sometimes even just 5%) can provide most of the precision and yield gains, compared to using the entire corpus. Note that the coverage-based checker has only a weak, second-order dependency on the statistical database. If no statistics are available to vet its results, the yield can only increase, with a decrease in precision.

Furthermore, when computing the statistical database, if we exclude all the 239 projects in the SRPM corpus that \( C_{1234} \) reports a warning on, the precision and recall are not affected much (see legend “excl”, both precision and recall are only slightly lower than when using the entire corpus). This observation answers \([4]\) b and confirms that the analysis is not over-fit to the specific projects within which it is reporting warnings.

**F. Discussion of triaged warnings**

Figure 8 compares the relative probabilities of a true-positive warning occurring at a call site with a given number of arguments. To compute these probabilities, we leave out call sites with less than two arguments, because it would not affect the relative probabilities shown here. We computed these probabilities as described for Figure 11 in \([4]\). In contrast to the probability distribution for Java programs \([4]\), we found that probability of true-positive warnings given a call site with two or three arguments is comparable to the probabilities of those with higher number of arguments. One possible explanation for the differences in the probability distributions could be that because C and C++ programs are “weakly typed”, it allows more room for confusion in ordering arguments, even when involving call sites with few arguments.

**G. Threats to validity**

Our techniques assume English names; it is unclear how much of our work is applicable to non-English names.

Our statistical database is derived from a mature open-source code corpus for the Linux platform, and this particular corpus may have good coding patterns, which is likely beneficial. However, we may have higher yield on projects that are less mature or yet-to-be released. Similar to a lot of work in this research area—where patterns are mined from code—our statistical vetting and the statistical checker makes the assumption that “most code is correct”. However, in specific domains, this assumption may not hold \([19]\). We give more importance to statistical patterns that occur across several projects, which may help assuage some concerns about our assumption. A possible area for improvement would be to recognize similar code in different projects and discount the statistics for occurrences across multiple similar projects. We do this deduplication (\(\S IV-A\)) at the granularity of entire files, which ignores many other forms of code duplication.

We expect our work to be applicable for several popular programming languages that support position-based arguments, other than C and C++; however, techniques in SWAPD may
not be useful for programs written in languages with keyword arguments, such as Smalltalk and Objective-C.

Finally, many of the warnings were triaged by people who developed SWAPD, which could have caused some bias in labeling warnings. One possible source of such bias is in the sampling of the warnings to triage. If the validity of a warning is difficult to ascertain, the triager may skip it and look for an easier one. However, difficult-to-triage warnings are more likely to be false positives, so skipping these would bias the triaged results toward more true positives.

V. RELATED WORK

In this section we discuss closely related previous work.

A. Matching argument and parameter names

The idea of detecting swapped-argument errors using mismatches between argument names and parameter names has been studied before [2], [4], [13]. Of these works, Rice et al. [4] have the most extensive real-world evaluation (run on 200 million lines of proprietary code, and 10 million lines of open-source code).

They detect incorrectly-ordered arguments at call sites in Java programs, and their work is most similar to our cover-based checker. They use string-similarity metrics on whole names to detect mismatched correspondences between arguments and parameters, whereas our cover-based checker performs morpheme-level reasoning. We believe that the cover-based checker is a better approach because it picks relevant signals from names being compared. Comparing whole names using a string distance is akin to comparing two whole sentences using a string distance: there is fundamental impedance mismatch; whereas using a cover-based checker is akin to comparing two sentences based on the words contained in them. Our approach is also readily extended to other morpheme-similarity measures, including considering synonymous morphemes to be equivalent. Their work will miss reporting bugs if parameter names are not available or not useful, whereas our hybrid approach can still report bugs in such cases based on mined statistical patterns. Their work will report false positives if there are function-specific anti-patterns that developers use (such as Listing 3), whereas we can filter out such warnings using statistical vetting.

B. Learning from code

With the increased availability of large amounts of code, learning models of “correct” code from existing programs and detecting anomalies as bugs [20] has been gaining popularity [21–25]. None of these [20–25] are mining name information for detecting swapped-arguments errors. We discuss our work in contrast to two such closely related works: DeepBugs [5] and APISan [26].

DeepBugs detects swapped-argument errors using a machine learning approach: they seed a corpus of programs with artificial likely swapped-arguments errors, and train a classifier to distinguish the artificial code from the unmodified real code. Because the real code is expected to have very few swapped-arguments errors, their hypothesis is that the classifier learns to identify swapped-arguments errors in real code. They apply their technique to JavaScript programs, with a corpus of 68 million lines of code. Their work is most similar to our statistical checker.

Their artificial seeding of swapped arguments in a corpus does not distinguish between intentional and unintentional swaps, and therefore, their classifier is unlikely to learn such a distinction. Determining whether a swap is intentional or not requires considering the surrounding code and context (e.g., preceding source text, conditionals, caller function), but such information is not taken into account by DeepBugs.

DeepBugs only considers swaps between the first two arguments at a call site, whereas we consider swaps between all pairs of arguments. DeepBugs requires a lot of training data; and it only reports warnings when the whole function name and the whole argument names (at first two positions) at a call site are all present in the top 10,000 vocabulary of names. DeepBugs reasons at the whole-name level, so call sites with less-frequently occurring whole argument names (that could be made of frequently-occurring morphemes) and function names are not even considered. Our morpheme-level reasoning boosts the signal present in name data for the statistical checker, and our hybrid approach can find bugs even when there is no statistical data available for a particular function.

Being able to explain why a warning is reported is an essential element for adoption. Explaining why DeepBugs predicted a call site to be buggy is hard [27], [28]. In contrast, our approach provides straightforward algorithmic explanations for each finding.

APISan detects various classes of errors by computing a statistical database of function-usage characteristics, and then finding anomalous patterns in the database. The characteristics they extract from arguments at a call site do not pertain to argument “names”. Instead, they focus on extracting and statistically reasoning about traditional semantic relations between argument values.

VI. CONCLUSION

In this paper, we have presented SWAPD, a technique to find mistakenly-swapped arguments at call sites. SWAPD exploits “big code” and carefully combines four stages (cover-based checker, statistical vetting, statistical checker, and false-positive filtering) to balance the precision and yield of the findings.

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REFERENCES

[1] VI Like Emacs. [Online]. Available: https://linux.die.net/man/1/xvil
[2] H. Liu, Q. Liu, C.-A. Staicau, M. Pradel, and Y. Luo, “Nomen est omen: Exploring and exploiting similarities between argument and parameter names,” in Proceedings of the 38th International Conference on Software Engineering, ser. ICSE ’16. New York, NY, USA: Association for Computing Machinery, 2016, p. 1063–1073. [Online]. Available: https://doi.org/10.1145/2884781.2884841
[3] GPaste. [Online]. Available: https://www.imagination-land.org/posts/2018-11-14-gpaste-3.3.0.2-released.html
[4] A. Rice, E. Attendantian, C. Jaspan, E. Johnston, M. Pradel, and Y. Arroyo-Paredes, “Detecting argument selection defects,” Proc. ACM Program. Lang., vol. 1, no. OOPSLA, Oct. 2017. [Online]. Available: https://doi.org/10.1145/3135392
[5] M. Pradel and K. Sen, “Deepbugs: A learning approach to name-based bug detection,” Proc. ACM Program. Lang., vol. 1, no. OOPSLA, Oct. 2017. [Online]. Available: https://doi.org/10.1145/3135392
[6] Fedora Package Sources. [Online]. Available: https://src.fedoraproject.org/
[7] GStreamer: open source multimedia framework. [Online]. Available: https://gstreamer.freedesktop.org/
[8] Grafx2. [Online]. Available: http://grafx2.chez.com/
[9] BoNeSi. [Online]. Available: https://github.com/Markus-Go/bonesi
[10] Mate Panel Libs. [Online]. Available: https://matplotlib.forth.kernel.org
[11] E. Enslen, L. Hill, M. Pollock, and K. Vijay-Shanker, “Mining source code to automatically split identifiers for software analysis,” in 2009 6th IEEE International Working Conference on Mining Software Repositories, 2009, pp. 71–80.
[12] Mate Panel Libs. [Online]. Available: https://pks.org/download/mate-panel-libs
[13] M. Pradel and T. R. Gross, “Name-based analysis of equally typed method arguments,” IEEE Transactions on Software Engineering, vol. 39, no. 8, pp. 1127–1143, 2013.
[14] GrammaTech, Inc. CodeSonar. [Online]. Available: https://www.grammatech.com/products/codesonar
[15] OASIS Static Analysis Results Interchange Format. [Online]. Available: https://www.oasis-open.org/committees/tc_home.php?wg_abbrev=starl
[16] OpenVAS Libraries. [Online]. Available: https://launchpad.net/ubuntu/+source/openvas-libraries
[17] Guilde. [Online]. Available: https://www.gnu.org/software/guilde/download
[18] XScreenSaver. [Online]. Available: https://www.jwz.org/xscreensaver/
[19] M. Egele, D. Brunley, Y. Fratantonio, and C. Kruegel, “An empirical study of cryptographic misuse in android applications,” in Proceedings of the 2013 ACM SIGSAC Conference on Computer and Communications Security, ser. CCS ’13. New York, NY, USA: Association for Computing Machinery, 2013, p. 73–84. [Online]. Available: https://doi.org/10.1145/2508859.2516693
[20] D. Engel, D. Y. Chen, S. Hallem, A. Chou, and B. Chelf, “Bugs as deviant behavior: A general approach to inferring errors in systems code,” in Proceedings of the Eighteenth ACM Symposium on Operating Systems Principles, ser. SOSP ’01. New York, NY, USA: Association for Computing Machinery, 2001, p. 57–72. [Online]. Available: https://doi.org/10.1145/502034.502041
[21] M. K. Ramanathan, A. Grama, and S. Jagannathan, “Static specification inference using predicate mining,” ACM SIGPLAN Notices, vol. 42, no. 6, pp. 123–134, 2007.
[22] P. Bian, L. Li, D. Zou, S. Xu, X. Ou, H. Jia, S. Wang, Z. Deng, and Y. Zhong, “Val deepecker: A deep learning-based system for vulnerability detection,” in 25th Annual Network and Distributed System Security Symposium, NDSS 2018, San Diego, California, USA, February 18-21, 2018. The Internet Society, 2018. [Online]. Available: http://wp.internetsociety.org/ndss/wp-content/uploads/sites/25/2018/02/ndss2018-03A-2_Li_paper.pdf
[23] Z. Li, D. Zou, S. Xu, X. Ou, H. Jia, S. Wang, Z. Deng, and Y. Zhong, “Valdeecker: A deep learning-based system for vulnerability detection,” in Proceedings of the 25th USENIX Conference on Security Symposium, ser. SEC’16. USA: USENIX Association, 2016, p. 363–378.
[24] C. Rudin, “Stop explaining black box machine learning models for high stakes decisions and use interpretable models instead,” Nature Machine Intelligence, vol. 1, no. 5, pp. 206–215, May 2019. [Online]. Available: https://doi.org/10.1038/s42256-019-0048-x
[25] DARPA. Explainable Artificial Intelligence. [Online]. Available: https://www.darpa.mil/program/explainable-artificial-intelligence
[26] Z. Li, D. Zou, S. Xu, X. Ou, H. Jia, S. Wang, Z. Deng, and Y. Zhong, “Valdeecker: A deep learning-based system for vulnerability detection,” in Proceedings of the 25th Annual Network and Distributed System Security Symposium, NDSS 2018, San Diego, California, USA, February 18-21, 2018. The Internet Society, 2018. [Online]. Available: http://wp.internetsociety.org/ndss/wp-content/uploads/sites/25/2018/02/ndss2018-03A-2_Li_paper.pdf
[27] I. Yun, C. Min, X. Si, Y. Jang, T. Kim, and M. Naik, “Apisan: Sanitizing api usages through semantic cross-checking,” in Proceedings of the 25th USENIX Conference on Security Symposium, ser. SEC’16. USA: USENIX Association, 2016, p. 363–378.