Do #ifdefs Influence the Occurrence of Vulnerabilities? An Empirical Study of the Linux Kernel

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ABSTRACT

Preprocessors support the diversification of software products with #ifdefs, but also require additional effort from developers to maintain and understand variable code. We conjecture that #ifdefs cause developers to produce more vulnerable code because they are required to reason about multiple features simultaneously and maintain complex mental models of dependencies of configurable code.

We extracted a variational call graph across all configurations of the Linux kernel, and used configuration complexity metrics to compare vulnerable and non-vulnerable functions considering their vulnerability history. Our goal was to learn about whether we can observe a measurable influence of configuration complexity on the occurrence of vulnerabilities.

Our results suggest, among others, that vulnerable functions have higher variability than non-vulnerable ones and are also constrained by fewer configuration options. This finding suggests that developers are inclined to notice functions that appear in frequently-compiled product variants. Our aim is to raise developers' awareness to address variability more systematically, since configuration complexity is an important, but often ignored aspect of software product lines.

1. INTRODUCTION

Diversification of software products is widely desired, but also induces challenges in development and maintenance processes of software product lines [21, 32]. Preprocessor directives (#ifdef statements) are frequently used as a mechanism to support code variability and thereby permit the diversification of software products. However, it is known that the presence of #ifdefs in source code complicates maintenance tasks and requires additional effort from developers when trying to understand feature code dependencies [20, 21, 35].

In this paper, we define *configuration complexity* as the complexity induced by the presence of #ifdefs in the code, and we conjecture that it causes developers to make mistakes that lead to more vulnerable code. Our assumption is motivated by the observation that humans have a limited capacity to keep an accurate and complete mental model of code dependencies [19]. When considering the scenario of maintaining multiple software products and reasoning about many variants simultaneously, this limitation could result in serious consequences. For example, it could cause unexpected feature interactions and feature code to be inadvertently executed or bypassed, creating opportunities for attackers to exploit software systems [31].

Figure 1 shows a snippet of a commit diff that fixed a vulnerability in file *arch/x86/kernel/traps.c* of the Linux kernel, a large configurable software system that shares many characteristics with industrial software product lines [13,36]. In this example, the #ifdef statement is used to constrain feature code according to the setting of two configuration options. Those are usually Boolean variables that represent features available in a product line and can be enabled or disabled in the application engineering process. In this example, function *do_stack_segment* is constrained by option *CONFIG_X86_64*, meaning that it will be compiled and be part of a product variant only when *CONFIG_X86_64* is enabled.

We seek to characterize configuration complexity of functions and analyze whether it associates with their past vulnerable behavior. To this end, we extract and quantify presence conditions (predicates over configuration options) from functions of the Linux kernel and use it as a baseline to compare samples of vulnerable and non-vulnerable functions. More than defining and quantifying configuration complexity, we aim at understanding whether the configuration aspect of unpreprocessed source code (i.e., the presence of #ifdefs in source code) provides additional information when used in combination with traditional size and structural complexity metrics [6, 25, 30].

Ultimately, we are interested in learning whether vulnerable and non-vulnerable functions have each distinguishable complexity characteristics that would potentially allow us to warn developers about critical pieces of a product line. We pose the following research questions:

RQ1 *Does configuration complexity associate with past vulnerable behavior of functions?*

RQ2 *Does configuration complexity provide additional insights about past vulnerable behavior of functions when compared to size and structural complexity?*

Our general hypothesis is that complexity metrics can help maintainers to identify vulnerability-prone code in configurable code. High configuration complexity can be used as

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a warning sign and, in concert with other quality indicators, could help to identify potential vulnerabilities, an important facet of what makes software difficult to assure.

Compile-time configuration complexity has not been considered in analyses before, because existing tools work on preprocessed code, that is, in a single configuration after running preprocessor and compiler. Even parsing unpreprocessed code soundly was a challenge that was only recently solved [10, 18]. Our infrastructure allows, for the first time, to parse (and type check) unpreprocessed code, while generating the call graph for all configurations of the Linux kernel. The produced *variational* call graph is an important basis for our analysis of configuration complexity of functions.

To define configuration complexity, we design three simple configuration complexity metrics (Section 4) that capture the complexity induced by the presence of #ifdefs in the code and three structural metrics that capture information on the relationship of functions in a call graph (Section 5).

Our results show that vulnerable and non-vulnerable functions have distinct characteristics regarding configuration complexity that can add additional value to traditional size and structural-complexity measures [6]. For instance, we found that vulnerable functions have, on average, three times more #ifdef statements inside them than non-vulnerable functions, an effect size greater than observable from studying size metrics only. For other measures of configuration complexity, we found similarly encouraging results. Our results provide a basis towards the development of prediction models, but more importantly, raise awareness of product-line developers to address variability more systematically (for example, with testing [9, 33] and variability-aware analysis [1, 38]).

Overall, we make the following contributions:

1. We define configuration complexity and provide an infrastructure to measure it on unpreprocessed C code.

2. We analyze how configuration complexity is associated with past vulnerable behavior of functions and investigate potential confounding effects between our metrics and traditional complexity metrics.

3. We discuss the general implications of our results for developers and maintainers of product lines.

2. BACKGROUND AND MOTIVATION

Based on existing work that suggests that the presence of #ifdefs in source code complicates maintenance tasks and requires additional effort from developers when trying to understand variable code dependencies [20, 23, 35], we aim at investigating the influence that code configurability has on the occurrence of vulnerabilities.

Configuration-related vulnerabilities arise in practice and, generally, can have serious consequences. One famous example is the Heartbleed vulnerability in OpenSSL (CVE-2014-0160), which affected servers, browsers, and many other systems that use this encryption library to secure Internet communication. In this specific case, the vulnerability was associated to one enabled-by-default configuration option that was frequently included in the build process, but rarely needed by users of the library.

Another example of a configuration-induced vulnerability was reported for the Linux kernel (CVE-2014-9322). In

```
236 -#ifdef CONFIG_X86_32
237  DO_ERROR(X86_TRAP_SS,     SIGBUS,  "stack segment",
    stack_segment)
238 -#endif
239  DO_ERROR(X86_TRAP_AC,     SIGBUS,  "alignment check",
    alignment_check)
240
241  #ifdef CONFIG_X86_64
242  /* Runs on IST stack */
243 -dotraplinkage void do_stack_segment(struct pt_regs *regs, long
    error_code)
244 -{
245 -       enum ctx_state prev_state;
246 -
247 -       prev_state = exception_enter();
248 -       if (notify_die(DIE_TRAP, "stack segment", regs,
    error_code,
249 -                      X86_TRAP_SS, SIGBUS) != NOTIFY_STOP) {
250 -               preempt_conditional_sti(regs);
251 -               do_trap(X86_TRAP_SS, SIGBUS, "stack segment",
    regs, error_code, NULL);
252 -               preempt_conditional_cli(regs);
253 -       }
254 -       exception_exit(prev_state);
255 -}
256 -
257  dotraplinkage void do_double_fault(struct pt_regs *regs, long
    error_code)
```

Figure 1: Snippet from the commit diff that fixed the CVE-2014-9322 vulnerability *(arch/x86/kernel/traps.c)*

this case, the code responsible for handling stack segment violations was distinct for different computer architectures (32-bit and 64-bit) and caused the 64-bit version to be vulnerable. Part of the solution to fix this vulnerability involved modifying the file *arch/x86/kernel/traps.c* by removing both the specialized function *do_stack_segment* responsible for handling error in 64-bit architectures (Lines 243 to 256) and the #ifdef directives responsible for applying the default error handling only to 32-bit architectures (Lines 236 and 238).

It has been observed that product line maintainers usually maximize the functionality of systems to reduce the high engineering costs required to certify every possible product variant that can be generated [37] and also rely on default values for configuration options to avoid the burden of reason about the complexity induced by code configurability [11]. The latter is even more dangerous because it increases the attack surface of software systems and, potentially, the number of undesired interactions among features [31].

To analyze #ifdefs, our analysis focuses on compile-time variability to enable systematic reasoning of code configurability [34, 39], rather than relying on sometimes useful, but unsound approximations, such as maximizing the configuration options enabled for a product or translating #ifdefs to if statements [39]. Moreover, it allows us to explore knowledge about configuration options that is sometimes buried in build files and macros, which makes it harder for developers to reason about its true effects without performing an in-depth analysis of unpreprocessed code.

The goal of our study was to use simple metrics that could capture our intuition of configuration complexity and allow us to search for evidence that the complexity induced by #ifdefs and configuration options associates with vulnerable behavior of functions. We define and operationalize the metrics in more detail in Sections 4 and 5.

One simple metric that we used to capture configuration complexity is the number of internal #ifdefs that appear

inside a function. Intuitively, this metric translates to how many times a maintainer would need to switch context between feature blocks (in addition to the conditional branches in the code), while trying to understand or modify a piece of configurable code.

Although this and other metrics are simple (Section 4), we believe they complement traditional size and structural complexity metrics, by augmenting individual function properties with other properties that originate from their interaction with other functions and their inherent variability.

When analyzing structural complexity, we aim at studying the phenomena that emerge from the interaction of program elements [15]. To this end, we extract a call graph from unpreprocessed code (Section 3.2) and maintain information about its variability by labeling functions (nodes) and function calls (edges). These labels, representing configuration complexity, are later quantified and used in combination with other numerical graph-based metrics. Ultimately, we expect to increase the usefulness of the traditional metrics [6].

3. EXPERIMENTAL SETUP

We decided on the Linux kernel (version 3.19, x86 architecture) as the subject of our study because it is one of the largest and most configurable product line publicly available for analysis [21] and, at the same time, one with the most reported vulnerabilities. With more than 14,000 configuration options available, the Linux kernel is widely used in industry and its use expands from high-end servers to mobile phones. From about 14,000 configuration options, only 8,537 affect our analysis of the x86 architecture.

In our experiment, we analyze the vulnerability history of functions, by checking whether a certain function has been touched by developers to fix past vulnerabilities. Next, we compute configuration complexity metrics for each function and analyze differences in samples of vulnerable and non-vulnerable functions along the selected metrics, such as the number of internal #ifdefs. To avoid fishing for results, we carefully design our metrics based on our understanding of how configuration complexity might affect developers; we discuss the metrics and their rationale in Sections 4 and 5.

In addition, we analyzed whether the configuration aspect of the code provides additional information when used in combination with traditional size and structural complexity metrics [6]. Our analysis considers the potential confounding effects of traditional complexity metrics and aims at understanding, quantifying, and isolating the real effect that #ifdefs have on the complexity of variable code.

3.1 Mining Vulnerabilities

To learn about whether configuration complexity of functions is associated with the occurrence of vulnerabilities, we needed to identify which functions have been vulnerable in the past. For this purpose, we mined reported known vulnerabilities from the National Vulnerability Database (NVD)[1]. This database catalogs information about real vulnerabilities that have been reported by developers and users when an exploit had been identified, each given a unique CVE number.

When investigating vulnerabilities, we collect information about the commits that have been assigned as responsible for fixing the code that was vulnerable in the past. That is, whenever code has been committed to fix a vulnerability, we identify all files and functions that have been modified in the commit.

From the vulnerability database, we identified 1,314 vulnerabilities reported from 1999 to 2015. For each vulnerability reported, we collected links to the commits fixing the vulnerability in the source code in either GitHub or kernel.org, resulting in a list of commits fixed reported vulnerability. For each commit in the list, we identify all files and functions that have been touched to fix a vulnerability.

We automated the extraction process to reduce human error. Specifically, we download the files from the commit diffs available in the commit, parse the C files using *srcML* [4], and then collect information about the location and boundaries of each function in the file (begin and end lines). Next, we use the function location to identify whether the changes have been made within the limits of a function. The result of this step is a list of functions that have been changed to fix each of the vulnerable files.

To increase our confidence in the extraction process and in the data we were extracting, we also decided to mine the history of commit messages directly from the Linux kernel git repository. We observed that some old reported vulnerabilities are not linked to git commits, so we assumed we could find information about vulnerable functions directly from commits that are not referenced in the vulnerability database. When analyzing the Linux kernel source code repository, we searched through the git history and looked for '*CVE-*' identifiers in commit comments. For each commit that matched with our search, we identified files and functions that have been modified by analyzing the textual diffs. We manually checked a few instances of the mined CVEs for correctness.

In total, we collected information on 1,314 CVEs, successfully parsed 11,956 files out of 12,075 files and extracted 233,903 functions of the Linux kernel (x86 architecture). From the set of extracted functions, 1,170 were associated with CVEs and are considered vulnerable; the remaining 232,733 functions are considered non-vulnerable.

3.2 Variational Call Graphs

We use variational call graphs to analyze the interactions among functions [15] and to investigate how configuration complexity influences those interactions. They serve as a technical basis for our structural complexity analysis (Section 5).

A call graph is an abstraction of a program that represents potential calls among functions at runtime. Although compact, call graphs are relatively cheap to compute and, yet, powerful abstractions of a program's behavior [7]. Besides being beneficial for developers to reasoning about software systems, call graphs are a useful approximation of a program's execution, which makes them potentially relevant to perform security-related program analysis [40].

To take configuration complexity into consideration, we extend the notion of call graph to make a variational call graph that compactly represents all possible function definitions and function calls of a given product line. The variational call graph provides the basis to analyze the effect of configuration complexity in graph-based metrics. Instead of producing a call graph for each individual system configuration, a variational call graph includes all possible nodes and

[1] https://nvd.nist.gov/

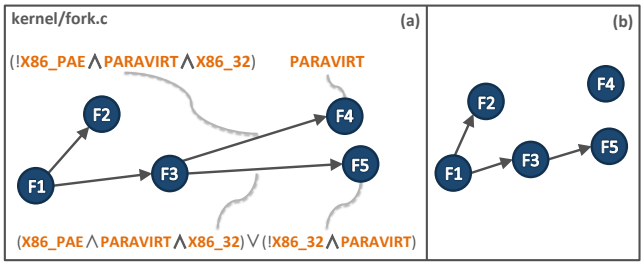


Figure 2: Excerpt of a variational call graph extracted from the Linux kernel *kernel/fork.c* file (a) and the resulting call graph when the configuration option *X86_PAE* is not selected (b). The presence conditions on nodes and edges in (a) show in which condition a function or function call would be included in a product variant.

edges of any system configuration, but labels each node and each edge with a *presence condition*, characterizing precisely in which configurations a function definition or function call would be included [22]. The result is a labeled graph that can be used for subsequent analysis; when analyzing configuration complexity, we are especially interested in these labels. Figure 2(a) shows an excerpt of the variational call graph for the file *kernel/fork.c* and the resulting call graph of a product variant when the configuration option *X86_PAE* is not selected (b).

To analyze configuration complexity, we first computed a variational call graph from the unpreprocessed source code of the Linux kernel (version 3.19, x86). To compute it, we implemented our analysis on top of the TypeChef infrastructure [17,18], which can parse unpreprocessed C code, including preprocessor directives, into a variational Abstract Syntax Tree (AST) representing all configurations. The nodes in the AST representation store the configuration information in the form of choice nodes [18]. By walking over the variational AST, we are able to identify function definitions and function calls that occur in the Linux kernel, as well as the presence conditions under which they are enabled or disabled from a product variant. To increase the accuracy of the call graph extraction, we implemented a relatively inexpensive but precise pointer analysis [7][1].

3.3 Null-hypothesis testing

The purpose of the tests is to check whether the samples of vulnerable and non-vulnerable functions are different according to the selected metrics that we will discuss in Sections 4 and 5. The null hypothesis for all tests is that both vulnerable and non-vulnerable functions are drawn from the same distribution of the metric.

For each metric, we performed a Welch two sample t-test between vulnerable and non-vulnerable function samples. We found significant differences in distributions and means between vulnerable functions and non-vulnerable functions for many of the selected metrics (Figure 4), where vulnerable functions are consistently more complex than non-vulnerable ones [2]. Also, we report both effect size (difference between means) and statistical significance for each metric, as well as an analysis of the validity of our t-test statistics. In addition to t-tests, we applied a confounding effect analysis to check whether our metrics are relevant to characterize complexity, by comparing them against existing ones such as size metrics (details can be found in an accompanying technical report [8]).

[1] https://github.com/ckaestne/TypeChef/

[2] Negative values on the x-axis are a consequence of smoothing the distribution curves for visualization purposes and should not be interpreted as valid metrics values.

```
1  #ifdef A
2  int foo(int v) {
3    int l = read_public_value();
4
5    #if defined(A) || defined(B)
6    l = read_private_value();
7    #endif
8
9    if (...) {
10     v = l + CONST_VALUE;
11   }
12
13   #ifdef C
14   assertEquals(v, l + CONST_VALUE)
15   #endif
16
17   return v;
18 }
19 #endif
```

Figure 3: Example of simple C code with preprocessor directives (#ifdefs).

4. SIMPLE CONFIGURATION-COMPLEXITY METRICS

We define configuration complexity as the complexity induced by the presence of #ifdefs in source code, and we select a number of metrics to quantify it. Quantifying configuration complexity is a challenging task. Our goal is to measure the effect that #ifdefs and configuration options have on developers when they have to understand or change a piece of configurable code as well as how these options influence them to make mistakes. To avoid fishing for results, we carefully designed a set of simple metrics that characterize our key intuitions of configuration complexity. Each of the following subsections presents an alternative metric to capture configuration complexity and its intuition, discusses the results of its null-hypothesis test, and reports an analysis of potential confounding effects associated with it.

4.1 (Number of) Internal #ifdefs

Our first approximation of configuration complexity is to simply count the number of #ifdefs that appear inside a function. Similar to *if* statements, #ifdef blocks can appear in many different forms in the code, that is, they can be nested, in sequence, or both. Our metric captures how many blocks of feature code, regardless of what configuration options are being used, a developer needs to reason about while trying to understand or modify a piece of variable code. While it ignores specifics about the variability inside a function, it captures the complexity generated by branches of variable code.

For the example, in Figure 3, there are two #ifdef blocks inside function *foo* (Lines 5–7 and 15–17), so the value of the metric is two. In this example, a developer would need to think about two blocks of variable code, one considering two configuration options (A and B, Line 5) and another considering just one (C, Line 15). The insertion of an #ifdef inside

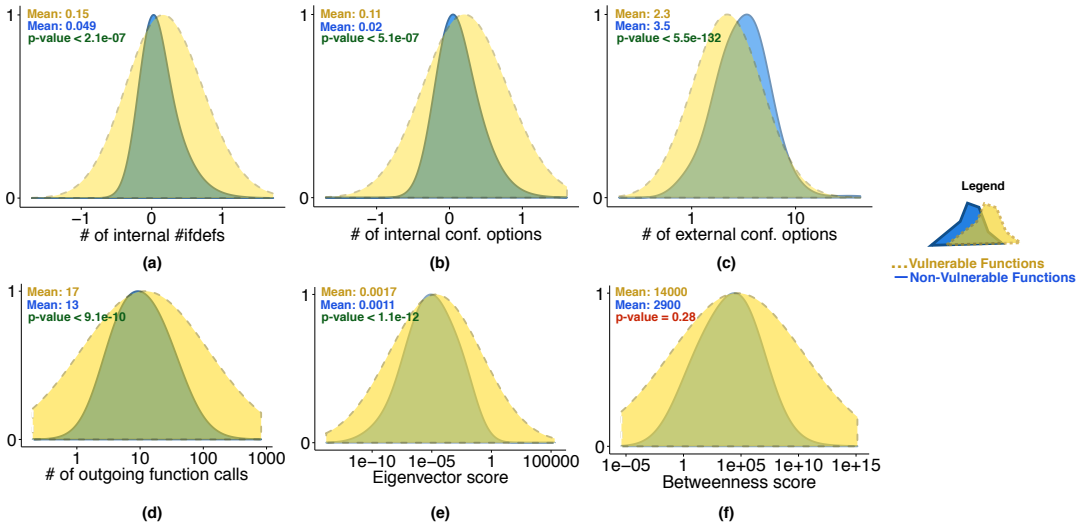


Figure 4: Density plots showing the distribution of vulnerable and non-vulnerable function samples along configuration complexity (first row) and structural complexity metrics (second row) in log_{10} scale.

a function, whether nested or in sequence to existing ones, would increase the configuration complexity of the code. An increase in the number of blocks of feature code inside a function would make a function more complex and more likely to be vulnerable.

Results

Our analysis reveals that vulnerable functions have, on average, 3.04 times more #ifdefs internally (0.15) than non-vulnerable functions (0.049); p < $2.1e^{-07}$; see Figure 4(a).

Confounding Effect Analysis

The correlation coefficient between the number of internal #ifdefs in a function and its size is 0.31, which suggests a moderate relationship between the two metrics, that is, long methods often tend to have more #ifdefs internally. When analyzing the regression coefficient for the internal #ifdefs metric before ($7.6e^{-09}$) and after the size metric is added to the regression model ($1.5e^{-10}$), we see small percentual change in the regression coefficient ($3e^{-07}$ percent), which indicates that there is no confounding effect between size and number of internal #ifdefs.

4.2 (Number of) Internal Configuration Options

Complementing the previous metric, our second approximation of configuration complexity counts how many distinct configuration options are used within a function. The intuition is that the higher the number of features affecting code inside a function, regardless of how many #ifdefs are in the function, the harder the code is to maintain, due to the increased number of configuration options a developer has to consider (remember the number of potential configurations grows exponentially with the number of options). In contrast to our previous metric, this metric captures configuration complexity by accounting for the amount of variability inside a function.

For the example in Figure 3, there are three distinct configuration options used in the two #ifdef blocks (A, B and C) inside the function *foo*, so the value of the metric is three. In this example, a developer would need to reason about how three features affect the piece of variable code he is trying to understand or modify.

Results

Our analysis reveals that vulnerable functions have on average 4.2 times more configuration options internally (0.11) than non-vulnerable functions (0.026), p <$5.1e^{-07}$; see Figure 4(b).

Confounding Effect Analysis

The correlation coefficient between number of configuration options used internally and function size is 0.17, which suggests a weak relationship between the two metrics. When analyzing the regression coefficient for the number of internal configuration options metric before ($-8.5e^{-08}$) and after the size metric is added to the regression model ($-3.5e^{-07}$), we see a small change in the coefficient ($7.6e^{-06}$ percent), which potentially indicates no confounding effect between number of internal configuration options and size.

4.3 (Number of) External Configuration Options

Different from the two previous metrics that consider how #ifdef blocks and configuration options affect the complexity *inside* a function, our third measure for configuration complexity considers the complexity of the presence condition that constrain the entire function. That is, this metric captures the chance that a function is included in a configuration in the first place. It counts how many distinct configuration options affect the decision whether a function is included in a product variant; technically, it counts the number of options inside #ifdef blocks *around* the function.[3]

[3]We do not only consider #ifdef blocks visible within the .c file, but also conditions from the build system and, often nontrivial, interactions among macro definitions, header inclusion, and conditional compilation [18, 27]. This analysis is more expensive and required significant infrastructure and engineering work, but is also much more precise than just scanning a file for #ifdef directives.

Our intuition is that the higher is the number of features required to activate a function and its corresponding file, the more complex is the condition to activate the code and, consequently, the less often the functionality is included in product variants. Functions that are only included in few configurations may be deployed less frequently, thus the chance of finding and exploiting a vulnerability is lower; but those functions may also receive less attention in the quality-assurance process, for example, fewer people might be interested during code review, leading to a higher chance of vulnerabilities in the future.

For the example of Figure 3, there is only one configuration option constraining function *foo(A)*, so the value of the metric is one. If a function was always included in all product variants, the metric value would be zero, since configuration has no effect on the presence or absence of the function.

Results

Our analysis reveals that non-vulnerable functions (3.5) are, on average, constrained by 1.5 times more configuration options than vulnerable functions (2.3), $p < 5.5e^{-132}$; see Figure 4(c).

Confounding Effect Analysis

We expect that the number of external configuration options is independent of the size of a function. The correlation coefficient between the two is 0.02, indicating no correlation. In addition, when analyzing the regression coefficient for the number of external configuration options metric before ($-3.2e^{-09}$) and after the size metric is added to the regression model ($-2e^{-09}$), we see a small percentual change ($3.7e^{-07}$ percent), which potentially excludes a confounding effect between the two metrics.

4.4 Summary

The results for the simple metrics defined in this section show that they capture distinct characteristics of configuration complexity. Despite some limitations of the metrics, including being naturally biased towards syntax rather than semantics and the existence of potential confounding size effects, they actually measure distinct characteristics of the variable code.

While we expected vulnerable functions to have more internal #ifdefs and more configuration options being used inside them, and consequently, to be more complex, we did not expect vulnerable functions to be constrained by fewer configuration options. We can speculate this happens because fewer configuration options are required to activate the presence of a function in a product variant and, due to broader exposure, more vulnerabilities have been found. Of course, we cannot claim anything about a specific configuration option, but assuming that all configuration options have the same chance of being enabled, requiring fewer configuration options would increase the chance of a function to be included in a product variant. That is, the chances of a function being exploited would increase along with frequency that it is included in product variants of the Linux kernel.

5. STRUCTURAL CONFIGURATION-COMPLEXITY METRICS

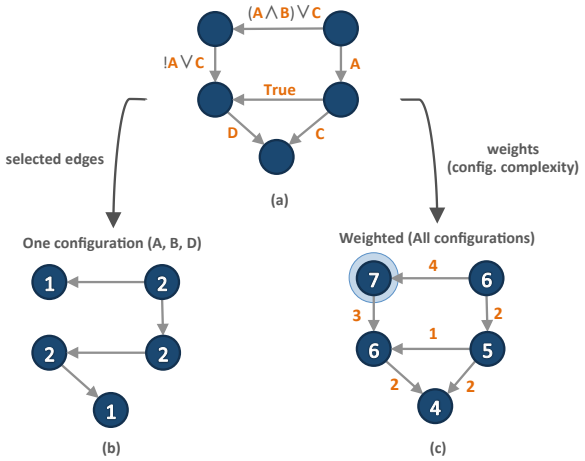


Figure 5: Example of a variational call graph with labeled edges representing presence conditions (a); a call graph produced by one specific configuration (when A, B, and D are selected) (b); and the call graph considering all configurations considering the quantification of configuration complexity as weights.

Whereas the previous metrics considered functions in isolation, our three *structural* configuration-complexity metrics characterize interactions among functions (represented by function calls) and capture how configuration options affect these interactions. All structural metrics are based on the variational call graph, introduced in Section 3.2, that compactly describes all potential call graphs for all configurations, in which functions (nodes) and function calls (edges) are constrained by presence conditions.

In all three structural metrics that we will present, we transform the presence conditions on edges into weights. Our intuition is that calls under very specific conditions are harder to reason about, so we give them a higher weight, roughly similar to a case where we would have many different calls between two functions. As weight, we use one plus the number of configuration options that control whether a call (edge) is included in a variant. In Figure 5(a,c), we show an example how edge weights are derived from the presence conditions in a graph.

Based on previous work [28, 42], we assume that graph-based metrics are a reliable proxy to measure the potential of interaction of nodes in a graph, and consequently, represent their structural complexity. We refine three metrics based on standard graph-based metrics [30] to capture different notions of centrality and, consequently, different notion of interactions among functions. The intuition behind these three metrics is that functions that interact, either directly or indirectly, with other functions under complicated configuration conditions, are more complex, and consequently, more prone to vulnerable behavior. That is, *we create graph-based metrics for configuration complexity based on traditional graph-based metrics by incorporating weights for configuration decisions and computing them over the entire configuration space*, not just a single product variant.

To separate the configuration aspect from the mechanism of the underlying graph-based metric, we compare each structural configuration-complexity metric to a corresponding baseline metric on a single configuration. For example, we compare the configuration-weighted eigenvector centrality met-

ric on the call graph for all configurations with an unweighted eigenvector centrality metric that we compute on the call graph on a single representative configuration. With this comparison, we can establish whether the configuration aspect provides additional information compared to traditional graph-based metrics [30]; Figure 5 illustrates that relationship.

As baseline, we use two configurations commonly used for quality-assurance tasks in Linux kernel: the default configuration (`'make defconfig'`) and the maximum configuration (`'make allyesconfig'`) Especially, the latter is frequently used to increase code coverage when testing or analyzing single product variants of the product line [38].

5.1 Degree Centrality

Our first metric combining structural and configuration-complexity is based on degree centrality [30], which measures the immediate importance of a node in the (weighted) graph by counting how many edges connect that node to other nodes. We consider both incoming and outgoing calls and add weights based on the number of external configuration options, as described above. We expect that functions with a high configuration-complexity value are called (or calling other functions) often and under complicated conditions, and are thus more difficult to understand and more likely to be vulnerable. Figure 5 shows how the configuration complexity aspect (represented as weights) changes the result of the metric computation compared to a baseline degree centrality metric on an unweighted call graph of a single variant.

Results

Our analysis on the complete call graph reveals that vulnerable functions have, on average, a 1.3 times more outgoing function calls (17) than non-vulnerable functions (13), $p < 9.1e^{-10}$; see Figure 4(d). That is they call more functions or call them under more complicated conditions. The analysis of incoming function calls was not statistically significant.

In comparison, the baseline metric on both the maximum and default configuration does not yield a statistically significant difference between vulnerable and non-vulnerable samples, but shows an increased difference of 0.91 and 0.85, respectively for maximum and default configuration. The results show that the addition of configuration complexity into the computation of degree amplifies the difference between the two sample means.

Confounding Effect Analysis

The correlation coefficients between our metric and the both baseline metrics for the two single configurations (maximum and default) are 0.0032 and 0.022 respectively, which suggests a weak connection between the two metrics.

When analyzing the change in odds of the regression coefficients of the weighted out-degree metric before ($1.8e^{-10}$) and after the out-degree metric from the maximum configuration is added to the regression model ($-6e^{-11}$), we see a small percentual change of the regression coefficient ($5.3e^{-07}$ percent). The weak correlation and confounding analysis results practically excludes a confounding effect between the metrics, which shows that considering configuration information improves the distinction of vulnerable functions and non-vulnerable ones.

5.2 Eigenvector Centrality

Our second structural configuration-complexity metric is based on eigenvector centrality, which is effectively a recursive version of the degree centrality, assigning higher values to nodes in neighborhoods of other nodes with high values [30]. Again, we compute eigenvector centrality on the weighted call graph of the entire configuration space and compare it against a baseline implementation of an unweighted graph of a single configuration. Our intuition is that this metric should be higher for functions with complicated conditional call relationships to other functions, especially in neighborhoods where many such complicated call relationships exist.

Results

Our analysis on the complete variational call graph reveals that vulnerable functions have, on average, an eigenvector score that is 1.5 times (0.0017) higher than non-vulnerable functions (0.0011), $p < 1.1e^{-12}$.

In comparison, the analysis on both the maximum and default configuration is not statistically significant. The results show that the addition of configuration complexity to the computation of eigenvector amplifies the difference between the two sample means and highlights the importance of taking configuration complexity into consideration; see Figure 4(e).

Confounding Effect Analysis

The correlation coefficients between our weighted eigenvector score (considering the number of configuration options that compose the presence condition on the edges) and the scores for the two single configurations (maximum and default) are 0.16 and 0.31, respectively. Similarly, this suggests a moderate correlation between the weighted and unweighted metrics on single configurations, which is expected as they are both computed with the same algorithm on similar inputs.

When analyzing the change in odds of the regression coefficients for the weighted eigenvector metric before ($-6.4e^{-13}$) and after the eigenvector metric from the maximum configuration is added to the regression model ($-4.9e^{-14}$), we see, again, a small percentual change of the regression coefficient ($1.3e^{-09}$ percent), which potentially excludes a potential confounding effect between the two metrics.

5.3 Betweenness Centrality

Our third structural configuration-complexity metric is based on betweenness centrality [30], which captures the notion of flow in the graph, an aspect that the two previous metrics do not address. Basically, it computes how many times a node acts as a bridge along the shortest path between two other nodes. In the context of variational call graphs, it can be interpreted as the influence potential of a function for causing global instability in the call graph. The function with the most strategic location, that is, the function that appears in most shortest paths of the call graph, is the most important one; note how this metric approximates the importance of a function in the runtime behavior of a program.

To consider configuration complexity, we incorporate the number of external configuration options that constrain the edge, and consequently modify the strength of alternative shortest paths (chain of function calls) between two other

functions. By considering configuration complexity, we intuitively reinforce shortest paths with more complex presence conditions. As baseline, we again compute betweenness centrality on the unweighted graph for two single configurations (maximum and default).

Results

Our analyses on the variational call graph on the maximum, and on the default configuration, are all not statistically significant. For this study, the results indicate that betweenness centrality has no sufficient discriminatory power to distinguish vulnerable from non-vulnerable functions. We therefore omit analyzing confounding effects; see Figure 4(f).

5.4 Summary

Overall, we conclude that the configuration complexity aspect of the metrics adds new information to traditional notions of structural complexity by amplifying the difference between the metric values for vulnerable and non-vulnerable functions. Our results show that combining configuration complexity and structural complexity metrics amplify the observed effect of degree- and eigenvector-centrality-based metrics, which signals to be worth paying attention to this combination.

6. DISCUSSION

We have shown that vulnerable and non-vulnerable functions in the Linux kernel have distinguishable characteristics regarding configuration complexity. This result provides a fresh view on the problem of understanding what causes vulnerabilities and whether there are measurable correlates that help us in avoiding vulnerabilities. The fact that static variability and preprocessors are widely used in practice has been largely ignored in this quest. Our study closes this gap.

A consequent next step is – in addition to understanding correlates of vulnerabilities in the presence of static variability – to explore whether we can deduce actionable insights in the form of approved coding guidelines or automatically quantifiable predictors. While a thorough treatment is well beyond the scope of this paper, we will discuss to what degree these insights might be used to predict vulnerabilities and guide quality-assurance effort, which additional characteristics might be measured to improve our metrics, and threats to validity to our analysis.

Vulnerability Prediction Challenges

A persistent modeling challenge is that vulnerable functions are extremely rare in the Linux kernel (1,170), not giving much information by which to compare them to non-vulnerable functions (232,733). While we can identify differing characteristics and ensure that they are not caused by the skewness of our data (see details in an accompanying technical report [8]), the difference may not be sufficient to predict at scale. Another issue that we faced is the unbalanced nature of the data. That is, in 96 percent of the cases functions do not have #ifdefs inside their scope. This combined with the fact that vulnerabilities are also rare events, make our task of analyzing effect sizes and building predictive models challenging.

We have explored logistic regression and discriminant analysis, but in both cases, the amount of noise and the unbalanced nature of the data contributed to a weak prediction model that, in 99 percent of the cases, predicted functions to be non-vulnerable. In that context, our metrics make measurable, but effectively tiny improvements to a predictor for vulnerability.

As a meta-result of our study, we arrived at the conclusion that, more than investigating new metrics, we have to develop and apply better statistical methods to take the specifics of the data we have at our disposal in to account, in particular, the skewness and availability of data.

As said previously, while ending on a sobering note with regard to predictability, our study nonetheless provides novel insights into the distinguishing characteristics of vulnerable functions in the presence of static variability – a dimension that has been overlooked for too long. More investigation is required to establish reliable thresholds for these metrics and to improve them to be used in predictive models.

Refining Configuration Complexity Metrics

While we have shown that even simple metrics, such as counting internal #ifdefs and configuration options used to constrain feature code, expose different characteristics of vulnerable and non-vulnerable functions, we expect that there are additional influence factors that could capture further aspects of configuration complexity.

For example, we could use analyze the importance of individual configuration options. Potentially, we could incorporate information about how and where configuration options are documented (for example, where in the hierarchy of a feature model [16]), how much code is affected by a configuration option, and how many developers have touched code a configuration option. With more information on configuration options used in practice (e.g., as in a recent study on configuration challenges [12]), we could even characterize how frequently certain configuration options are included in product variants used (and tested but also exploitable) in practice. In addition, with information about developers (e.g., developer/code networks [14]), we could identify which options have been developed by groups of experienced developers in a domain familiar to them.

We believe that there are many characteristics of variability left to explore. For instance, in an exploratory analysis, we found that the presence conditions of a major part of vulnerable functions usually contain only few configuration options, and that these options are often defined near the top of the feature model. This result may corroborate that functions frequently included in the build process are being noticed and more frequently screened for vulnerabilities. We think our study on configuration complexity contributes to making variability information more accessible. Ultimately, when able to understand complexity metrics and their associated thresholds, we envision the creation of a dashboard that aggregates other quantitative information on variability (as discussed in the literature [2,12,14,41]) to better support product line maintainability.

Threats to Validity

We acknowledge that we cannot generalize and claim representativeness from our single case study of the Linux Kernel. Nonetheless, we have selected the Linux kernel because it is an important case of a product line and also the one with the largest number of reported vulnerabilities. For example, OpenSSL has a much smaller code base and only 139 reported vulnerabilities available for analysis.

Our extraction process can potentially threaten the validity of our conclusions. For instance, when investigating the vulnerability history of functions, we rely on the vulnerability database completeness and on CVE reports and commits accuracy, which are both produced by humans and are consequently subject to human error. Also, we discard information of multiple appearances of a function in the vulnerability history and consider only whether a function was once vulnerable or not. This way, we lose potentially important information on code churn, but also simplify the analysis.

We use third-party software to parse and extract simple size metrics from C code (srcML [4]), and to calculate graph-based metrics (igraph [5]). Issues could arise if, for example, the parser is tricked by unusual and obscure use preprocessor directives. From prior studies, we know that these cases are rare, though [21].

As discussed, our analysis results suffer from the high skewness of the data. The rareness of the events we are interested in, such as, the number of vulnerable functions and the number of #ifdefs used inside functions, required us to be careful when using statistical techniques for data analysis. We addressed this as far as possible with corresponding analyses throughout the paper (e.g., checking the validity of the t-test [8]). Finally, our configuration-complexity metrics are only proxies for actual configuration complexity. For this reason, we explicitly control for potential confounding effects between our metrics and existing size and structural complexity ones [6, 30].

7. RELATED WORK

Challenges in developing and maintaining variable code with preprocessors are frequently discussed in the literature [20, 23, 26].Researchers state that developers struggle in understanding source code with variability because it is hard to keep track of the data-flow and control-flow dependencies and precisely identify what parts of the code are actually going to be compiled into a product variant. Medeiros et al. [26] have interviewed developers that use the C preprocessor in practice and found that they frequently suffer from preprocessor-related problems and bugs [1]. Despite all known challenges, developers do not see alternative technologies that could satisfactorily replace the C preprocessor, which indicates that it will continue being used as a main tool to implement variability. Configuration-related issues have also been discussed as a severe security threat to software systems [31].

Similar to our work, Chowdhury et al. [3] investigated the connection between *code* complexity metrics and the occurrence of vulnerabilities. Their results suggest that code complexity metrics can be dependably used as early indicators of vulnerabilities in software systems. Our work complements their work by defining *configuration complexity* metrics, which capture different aspects of complexity, and also in checking whether these metrics can be used as reliable indicators of vulnerabilities.

Neuhaus et al. [29] investigated the sources of vulnerabilities in software systems. The authors report that components that share similar sets of function calls are likely to be vulnerable. We explore this notion by identifying functions that are called under many different configuration options and have more complex interactions. More sophisticated metrics have been proposed as an alternative to capture complexity of software systems by using graph-based representations [24, 42].

One strategy used by many analyses is to simply ignore all configuration-related constructs in the source code and to analyze the system after the code has been preprocessed, that is, without configuration information (e.g., either generating a product variant by maximizing the number of features enabled or relying on a default configuration) [38]. Although useful in some cases, since developers can reuse existing tools, this strategy produces incomplete results and do not allow them to reason about the configuration options and their effects on the system in a systematic fashion. To address this limitation, many researchers recently investigated family-based (or variability-aware) analysis across entire configuration spaces [38]; our mechanism to build variational call graphs is an instance of that line of research.

8. CONCLUSION

Preprocessors directives (#ifdefs) have a bad reputation when maintainability and comprehension are first priorities for product-line maintainers. We investigated the influence of configuration complexity on the occurrence of vulnerabilities; our results suggest, among others, that vulnerable functions have, on average, three times more internal #ifdefs than non-vulnerable ones. In addition, vulnerable functions are constrained by fewer configuration options, which suggests that developers are inclined to notice functions that are frequently compiled in product variants. Our goal is to raise the awareness of developers to handle code variability more systematically, since it is an important, but often ignored, aspect of product-line engineering.

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