# MetricHaven – More Than 23,000 Metrics for Measuring Quality Attributes of Software Product Lines

Sascha El-Sharkawy University of Hildesheim, Institute of Computer Science Hildesheim, Germany elscha@sse.uni-hildesheim.de Adam Krafczyk University of Hildesheim, Institute of Computer Science Hildesheim, Germany adam@sse.uni-hildesheim.de Klaus Schmid University of Hildesheim, Institute of Computer Science Hildesheim, Germany schmid@sse.uni-hildesheim.de

# ABSTRACT

Variability-aware metrics are designed to measure qualitative aspects of software product lines. As we identified in a prior SLR [6], there exist already many metrics that address code or variability separately, while the combination of both has been less researched. MetricHaven fills this gap, as it extensively supports combining information from code files and variability models. Further, we also enable the combination of well established single system metrics with novel variability-aware metrics, going beyond existing variability-aware metrics. Our tool supports most prominent single system and variability-aware code metrics. We provide configuration support for already implemented metrics, resulting in 23,342 metric variations. Further, we present an abstract syntax tree developed for MetricHaven, that allows the realization of additional code metrics. Tool: https://github.com/KernelHaven/MetricHaven

Video: https://youtu.be/vPEmD5Sr6gM

# CCS CONCEPTS

• General and reference  $\rightarrow$  Metrics; • Software and its engineering  $\rightarrow$  Software product lines; Automated static analysis.

### **KEYWORDS**

Software Product Lines, SPL, Metrics, Implementation, Variability Models, Feature Models

### ACM Reference Format:

Sascha El-Sharkawy, Adam Krafczyk, and Klaus Schmid. 2019. MetricHaven – More Than 23,000 Metrics for Measuring Quality Attributes of Software Product Lines. In 23rd International Systems and Software Product Line Conference - Volume B (SPLC '19), September 9–13, 2019, Paris, France. ACM, New York, NY, USA, 4 pages. https://doi.org/10.1145/3307630.3342384

#### **1** INTRODUCTION

In software engineering, metrics are an established approach to characterize properties of software [7]. However, variability management is a key part of Software Product Lines (SPLs), which is not covered by traditional metrics. The SPL research community developed variability-aware metrics to address this issue, which received increasing attention over the last decade [5]. While a few very specialized metrics have been integrated into SPL-specific IDEs, there is still a lack of publicly available metric tool suites. Here, we introduce MetricHaven, an extension of KernelHaven [12], for the flexible execution and combination of variability-aware code metrics.

MetricHaven provides support for the measurement of traditional code metrics that ignore variability, SPL metrics that measure only variability, and the combination of both. Further, we allow the flexible combination of variability-aware code metrics with feature metrics, e.g., to detect complexity that arises through the combination of the variability model and code artifacts. MetricHaven provides configuration support to select among 23,342 metric variations (as of spring 2019). This is achieved by a specialized Abstract Syntax Tree (AST), which covers relevant information for measuring this broad variety of metrics. Through the underlying architecture of KernelHaven, which is optimized for parallelization, MetricHaven is able to measure a small number of selected code metrics on the whole Linux Kernel in less than 5 minutes, while the computation of all 23,342 metric variations takes around 3,5 hours. This means that in average each metric requires less than 1 second to measure the complete source code of Linux.

We regard MetricHaven as an experimentation workbench [11] for the analysis of SPL metrics. The provided concepts support researchers in developing and evaluating new variability-aware metrics. More precisely, we plan to analyze the potential of the metrics for fault prediction, by applying machine learning on the produced data. Also, practitioners may benefit from MetricHaven as they can directly use the tool for the detection of code smells.

# 2 CONCEPT

MetricHaven supports metrics for single systems, variability-aware metrics for SPLs, and arbitrary combinations of both. Further, we allow the combination of feature metrics for variability-aware metrics, if they count the number of features as part of their computation. As a result, MetricHaven supports more than 23,000 metric variations. Below we list the most important design decisions of MetricHaven:

**Decoupling of Parsers and Metrics.** The underlying architecture of KernelHaven provides data models, which serve as input for different kind of analyses [12]. This allows reuse of extractors and data models for the realization of new analyses. For the implementation of MetricHaven, we could benefit from existing extraction capabilities for variability and build models. The extraction of the variability model and its data model required minor adaptations for storing hierarchy information, which serve as input for some of the feature metrics. Only new extractors are required for measuring product lines that use modeling techniques that are not supported so far.

**Common AST.** To allow the arbitrary implementation of single system and variability-aware code metrics, we require one common AST that stores elements of the annotation language, e.g.,

SPLC '19, September 9-13, 2019, Paris, France

<sup>© 2019</sup> Copyright held by the owner/author(s). Publication rights licensed to ACM. This is the author's version of the work. It is posted here for your personal use. Not for redistribution. The definitive Version of Record was published in 23rd International Systems and Software Product Line Conference - Volume B (SPLC '19), September 9–13, 2019, Paris, France, https://doi.org/10.1145/3307630.3342384.

SPLC '19, September 9-13, 2019, Paris, France



Figure 1: Excerpt of MetricHaven's AST.

C-preprocessor, and elements of the programming language, e.g., C statements<sup>1</sup>. This is a challenging task, since the preprocessor is not part of the programming language and can be used at arbitrary positions inside a code file, independently of any syntax definitions. On the other side, we do not need a syntactical correct and complete AST, since the AST should not be used for compilation tasks or type checking analyses. Figure 1 presents an excerpt of our AST, which was motivated by our systematic literature study on variability-aware metrics [6] and an informal survey on traditional code metrics. The two most import elements are:

- The CppBlock is used to store preprocessor blocks (#if, #ifdef, #ifndef, #elif, #else). Since it inherits from two classes (ICode and CodeElementWithNesting), it allows the insertion of preprocessor directives at arbitrary positions in our AST.
- The SingleStatement is the most fine-grained element of our AST, which is sufficient for the measurement of the most prominent metrics. Expressions are stored as unparsed elements.

**Preprocessing Framework.** The metric calculation operates on a per-function basis. This simplifies the implementation of metrics and also creates parallelization opportunities. However, some metrics (e.g. the Fan-In/-Out and Scattering Degree metrics) require a complete view on the whole code. For this, we implemented pre-processing components that run before the metric computation on the full models supplied by the extractors. The results of these pre-processing components are passed to the metric calculation component, which can look up these pre-calculated values.

# 2.1 Variability-aware Code Metrics

The AST given in Figure 1 stores enough information to realize traditional code metrics for single systems, variability-aware metrics for SPLs, and arbitrary combinations of both. Below, we present currently realized metrics, which may be selected by users to measure properties of SPLs (cf. Section 3). However, these metrics are not complete as the AST supports the definition of further metrics.

**McCabe's Cyclomatic Complexity Measure** [15] is a very common metric for single systems that computes the number of linear independent paths of the control flow representation. This may be computed by adding 1 to the sum of all branching statements (if, while, for, case, ...) [3]. This approach was also applied to variation points to measure complexity of variation points [14]. We support three alternatives to compute the cyclomatic complexity: The first counts only branching statements of the

programming language. The second counts only variation points, e.g., #ifdef-blocks. The last one counts both kinds of branching statements, independently whether branching statements of the programming language are repeated in multiple variation points.

**Nesting Depth (ND)** measures the maximum / average nesting level of statements within control structures [3]. The authors argue that each nesting increases the complexity as a developer needs to consider all enclosing conditions when editing the code. This concept was also applied to variation points [13]. We support three variations of this metric by counting the nesting depth of statements of the programming language, variation points, and the combination of both.

**Fan-In/-Out** metrics are designed to trace how data is processed inside a program [3]. Ferreira et al. [8] designed metrics that measure the incoming and outgoing connections of functions in combination with the number of features used for the selection of these connections. Based on these metrics, we defined 3 variations of *Fan-In/-Out* metrics. The first variation measures only connections between functions and ignores the variability of the code. The second variation counts only conditional connections, that are function calls surrounded by at least one variation point inside the function. The third variation counts the number of features used to control the conditional inclusion of a function call.

**Lines of Code (LoC)** measures are very important metrics for single systems, but also in the context of SPLs. There exist a plethora of interpretations how to measure LoC. Jones [10] recommended to count statements instead of lines in order to have a formatting independent measure. *Lines of Feature code (LoF)* measures the lines of code that are controlled by a variation point [13]. In addition, the *Fraction of Annotated Lines of Code (PLoF)* computes  $\frac{\text{LoF}}{\text{LoC}}$ . We support LoC, LoF, and PLoF on statement level. Please note that the data model given in Figure 1 also conceptually supports to measure the lines of code instead of statements, as we also store the start and end line of each element.

**Features per Function** are designed to measure the complexity induced by the presence of #ifdef-blocks in the code [8]. We implemented 5 variations: 1.) Measures the number of features used inside a function. 2.) Measures the number of features that control the presence of the function, *excluding* the build model. 3.) Measures the number of features that control the presence of the function, *including* the build model. 4.) The union of the first and second metric. 5.) The union of the first and third metric.

Blocks per Function measure the number of variation points, instead of the features, used inside a code function [8]. The authors do not specify whether #else/#elifs are treated as separate blocks or as part of the #ifdef-block. For this reason, we implemented two variations of this metric: The first metric counts only the number of #ifdef-blocks and ignores its siblings. The second treats related #else/#elifs as separate blocks.

**Tangling Degree (TD)** counts the number of features used in variation point expressions [13]. We realized only one version, as we do not know about a relevant variation of it.

<sup>&</sup>lt;sup>1</sup>The concepts we propose here, could also be applied well beyond C.

MetricHaven - More Than 23,000 Metrics for Measuring Quality Attributes of SPLs

# 2.2 Feature Metrics

MetricHaven allows a flexible combination of code metrics with feature metrics. This can be done since most of the variabilityaware code metrics count the number of features used to control the variation points. For these metrics we allow the usage of a feature metric to measure the complexity of the variation point instead of counting the number of used features only. Below, we introduce 7 feature metrics. Most of them are based on existing measures, but we developed also some new metrics for unmeasured properties.

**Scattering Degree (SD)** metrics are used to analyze whether a feature is implemented in a modularized way (low scattering) or is spread over the code base (high scattering) [17]. A high scattering indicates a fragile design and may significantly increase system maintenance. We re-implemented two variations:  $SD_{VP}$ [13] is a commonly used metric that counts the number of variations points (i.e., #ifdef-blocks) a feature is used in.  $SD_{File}$ [9] is a more coarse-grained version as it counts the number of code files, in which a feature is used in at least one variation point.

**Feature Size** is inspired by the LoF-metric of the previous section. We count for each feature the statements controlled by that feature. We count a statement to all features that (in-)directly control the inclusion of the statement. For instance, the statements in Lines 3–5 of Figure 2 are controlled by the feature *A*. The idea of this metric is to provide an alternative to the previously defined scattering degree metric, which shows the impact of a feature to the implementation of the SPL.

The **Number of Constraints (NoC)** metric [1] is often used to measure the complexity of feature models, by counting the number of cross-tree constraints. We refined this metric and provide 3 feature metric derivations: NoC counts the number of all constraints of the feature model, where the respective feature is used in. Some modeling approaches allow a differentiation among constraints, e.g., the modeling approach of Linux requires that constraints are modeled as attributes of features [4]. We allow a separate analysis of constraints modeled as attributes of a feature (NoC<sub>out</sub>) and constraints of other features referring to the measured feature (NoC<sub>in</sub>).

The **Coefficient of Connectivity-Density (CoC)** is designed to measure how well graph elements are connected [1]. This is done by dividing the number of edges (parent child relations and constraints) by the number of features in a feature model. We modified this metric to operate on features instead of the complete feature model only and provide two alternative measures: The first alternative counts the number of non-transitive child features, to measure the number of parent-child edges. We do not count the parents, since it would increase all numbers by one only, excerpt for the root feature. The second alternative considers also all incoming and outgoing constraint connections, which are also measured by the NoC-metric of the previous Section.

The **Feature Types** metric is inspired by work that analyzes the amount of non-Boolean features used in publicly available SPLs [16]. We allow to specify weights for each feature type. This facilitates an analysis whether the usage of non-Boolean features in variation points increases the code complexity.

**Feature Hierarchies** is inspired by work on how structural properties impact the complexity of feature models. This includes the measurement of the depth of tree, the number of top features,



Figure 2: Code example and its variable control-flow.

or the number of leaf features [1]. We support two variations of hierarchy-based feature metrics: The first variation uses the nesting level of the feature as a feature metric. The second variation allows user-defined weights for top-level, intermediate, and leaf features.

This **Feature Locality** metric is a novel metric designed for the modeling behavior of Linux. Its variability model is spread over several hundred files [2]. The used include mechanism provides a modularization concept at which a sub feature-model can be stored at the same location as the realizing implementation. In addition, it is possible to provide alternative sub feature-models containing the same features with different constraints for different CPU architectures. We provide a feature metric to measure the distance of a feature realization and the feature definition. This is done by computing the distance in the file system of the sub feature model that defines the feature and the measured code artifact, which uses the respective feature. If the feature is defined by multiple alternative files, we count the shortest distance.

### 2.3 Example

Based on the variable control flow representation shown in Figure 2, we demonstrate how MetricHaven supports the computation of McCabe's cyclomatic complexity metric [15] as well as the variability-aware version of the metric [14]. Further, we demonstrate how to combine the variability-aware code metrics presented in Section 2.1 with feature metrics presented in Section 2.2.

**McCabe on Code.** McCabe's metric [15] computes the linear independent paths of the control flow representation of a program. Our example contains two linear independent paths, drawn with black lined arrows. This can be counted by adding 1 to the number of Branch- and LoopStatements.

**McCabe on Variation Points.** The variability-aware version of McCabe considers only paths created by variation points [14]. The example contains two paths. The black lined arrows are treated as one path (keeping the #ifdef-block) and the blue dotted arrows (removal of the #ifdef-block). This can be counted by adding 1 to the number of CppBlocks.

**McCabe on Variation Points and Code.** Further, MetricHaven allows a combination of the single system and the variability-aware code metric in a manner, which was not done before. For the combination of both metrics, we need to count all three paths of the control flow graph.

**Combination with Feature Metrics.** McCabe proposed to treat compound expressions in the form of  $Exp_1$  and/or  $Exp_2$  as separate paths as they could alternatively be realized with multiple if-then-else blocks [15]. Following his idea, we support measuring

of features in conditions rather than counting variation points only. Instead of adding 1 for each measured feature, we add the complexity value of a selected feature metric of Section 2.2. For example, we facilitate using the number of modeled constraints (NoC-metric) in which feature A appears in instead of counting the blue dotted path.

### 3 USAGE

MetricHaven is implemented as a plug-in for the KernelHaven infrastructure, which requires the Java runtime version 8 or higher. We recommend at least 16 GiB of RAM for the computation of all 23,342 metric variants. The default release of KernelHaven includes MetricHaven and required extractors for analyzing the Linux Kernel up to version 4.17. The variability and build model extractors work only on a Linux system with an installed GCC compiler plus the prerequisites for compiling the Linux Kernel. Other extractors may be supplied as additional plug-ins that allow analyzing other SPLs, which may not have these limitations.

An execution of MetricHaven requires a KernelHaven release<sup>2</sup> to be downloaded and unpacked. The release includes the code\_metrics.properties configuration file, which can be used as a basis for the execution of MetricHaven. The KernelHaven process is started with the following command<sup>3</sup>:

java -jar KernelHaven.jar code\_metrics.properties

KernelHaven's pipeline and the analysis components may be configured via Java properties files. The most relevant settings with respect to MetricHaven are:

- source\_tree specifies the path to the SPL to analyze. For example, this can be the root directory of an unpacked Linux Kernel.
- By default, all 23,342 metric variations are executed. metrics. .code\_metrics may be used to select all variations of one metric. The provided configuration file contains a list of supported metrics. Further, metrics.function\_measures.all\_variations may be used to select a single metric variation.
- code.extractor.threads controls the number of threads used for parsing the source code of the product line.
- metrics.max\_parallel\_threads controls the number of threads used for calculating the metrics for a single function. This may be used for the computation of a large number of metric variations, otherwise the overhead of multithreading is too high.

# 4 CONCLUSION

We presented MetricHaven, an extension of KernelHaven for measuring metrics for single systems, variability-aware metrics for SPLs, and arbitrary combinations of both. Further, it supports the combination of feature metrics with variability-aware code metrics. Its flexibility allows the combination of 23,342 metric variations. This is achieved by an common AST that combines information of parsed code annotations (e.g., C-preprocessor) and the programming language (e.g., C-code).

MetricHaven is very fast. For example, it requires 3,5 hours for measuring all 23,342 metric variations on the complete Linux kernel<sup>4</sup>. This is about half a second per metric. Or, to put it differently, measuring 23,342 metrics, requires about 40ms per code function. MetricHaven is a publicly available experimentation workbench designed to support researchers and practitioners in the analysis of annotation-based SPLs. New metrics may be developed based on the presented AST, without the need to develop new parsers. On the other side, the existing metrics may be applied without any changes to other imperative code files through the implementation of new extractors. This supports researchers in evaluating new SPL metrics. Also practitioners may benefit from MetricHaven as they can directly use the tool for the detection of code smells of annotation-based SPLs.

# ACKNOWLEDGMENTS

This work is partially supported by the ITEA3 project REVaMP<sup>2</sup>, funded by the BMBF (German Ministry of Research and Education) under grant 01IS16042H. Any opinions expressed herein are solely by the authors and not of the BMBF.

### REFERENCES

- Ebrahim Bagheri and Dragan Gasevic. 2011. Assessing the Maintainability of Software Product Line Feature Models Using Structural Metrics. Software Quality Journal 19 (Sep 2011), 579–612. Issue 3.
- [2] Thorsten Berger, Steven She, Rafael Lotufo, Andrzej Wąsowski, and Krzysztof Czarnecki. 2013. A Study of Variability Models and Languages in the Systems Software Domain. *IEEE Trans. Software Eng.* 39, 12 (Dec 2013), 1611–1640.
- [3] Samuel D. Conte, Herbert E. Dunsmore, and Vincent Y. Shen. 1986. Software Engineering Metrics and Models. Benjamin-Cummings Publishing Co., Inc.
- [4] Sascha El-Sharkawy, Adam Krafczyk, and Klaus Schmid. 2015. Analysing the Kconfig Semantics and Its Analysis Tools. In Proceedings of the 2015 ACM SIGPLAN International Conference on Generative Programming: Concepts and Experiences (GPCE 2015). 45–54.
- [5] Sascha El-Sharkawy, Adam Krafczyk, and Klaus Schmid. 2017. An Empirical Study of Configuration Mismatches in Linux. In Proceedings of the 21st International Systems and Software Product Line Conference – Volume A (SPLC '17). 19–28.
- [6] Sascha El-Sharkawy, Nozomi Yamagishi-Eichler, and Klaus Schmid. 2019. Metrics for analyzing variability and its implementation in software product lines: A systematic literature review. *Information and Software Technology* 106 (2019), 1–30.
- [7] Norman Fenton and James Bieman. 2014. Software metrics: a rigorous and practical approach. CRC Press.
- [8] Gabriel Ferreira, Momin Malik, Christian Kästner, Jürgen Pfeffer, and Sven Apel. 2016. Do #Ifdefs Influence the Occurrence of Vulnerabilities? An Empirical Study of the Linux Kernel. In 20th International Systems and Software Product Line Conference (SPLC '16). 65–73.
- [9] Claus Hunsen, Bo Zhang, Janet Siegmund, Christian Kästner, Olaf Leßenich, Martin Becker, and Sven Apel. 2016. Preprocessor-based Variability in Open-source and Industrial Software Systems: An Empirical Study. *Empirical* Software Engineering 21 (Apr 2016), 449–482. Issue 2.
- [10] Capers Jones. 1986. Programming Productivity. McGraw-Hill, Inc.
- [11] Christian Kröher, Sascha El-Sharkawy, and Klaus Schmid. 2018. KernelHaven – An Experimentation Workbench for Analyzing Software Product Lines. In Proceedings of the 40th International Conference on Software Engineering: Companion Proceedings (ICSE '18). 73–76.
- [12] Christian Kröher, Sascha El-Sharkawy, and Klaus Schmid. 2018. KernelHaven – An Open Infrastructure for Product Line Analysis. In Proceedings of the 22nd International Systems and Software Product Line Conference – Volume 2 (SPLC '18). 5–10.
- [13] Jörg Liebig, Sven Apel, Christian Lengauer, Christian Kästner, and Michael Schulze. 2010. An Analysis of the Variability in Forty Preprocessor-based Software Product Lines. In 32nd ACM/IEEE International Conference on Software Engineering – Volume 1 (ICSE '10). 105–114.
- [14] Roberto E. Lopez-Herrejon and Salvador Trujillo. 2008. How complex is my Product Line? The case for Variation Point Metrics. In Second International Workshop on Variability Modelling of Software-Intensive Systems (VAMOS'08). 97–100.
- [15] Thomas J. McCabe. 1976. A Complexity Measure. IEEE Trans. Software Eng. SE-2, 4 (1976), 308–320.
- [16] Leonardo Passos, Marko Novakovic, Yingfei Xiong, Thorsten Berger, Krzysztof Czarnecki, and Andrzej Wąsowski. 2011. A Study of non-Boolean Constraints in Variability Models of an Embedded Operating System. In 15th International Software Product Line Conference, Volume 2 (SPLC '11). 2:1–2:8.
- [17] Leonardo Passos, Rodrigo Queiroz, Mukelabai Mukelabai, Thorsten Berger, Sven Apel, Krzysztof Czarnecki, and Jesus Padilla. 2018. A Study of Feature Scattering in the Linux Kernel. *IEEE Trans. Software Eng.* (2018), 1–1.

<sup>&</sup>lt;sup>2</sup>https://github.com/KernelHaven/KernelHaven

<sup>&</sup>lt;sup>3</sup>More details in appendix of https://sse.uni-hildesheim.de/en/research/publications/p ublikation-einzelansicht/?lsfid=41623&cHash=b244065d45b8c85e2cd7560559dda3dd <sup>4</sup>Measurement of Linux version 4.15 on 2 Xeon E5-2650 v3 with 128 GB memory