Technische Universität Braunschweig

Department of Computer Science

Master's Thesis

Assessing Performance Evolution Of Configurable Software Systems

Untersuchungen zur Performanz-Evolution von konfigurierbaren Software-Systemen

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Eidesstattliche Erklärung

Hiermit versichere ich an Eides statt, dass ich die Arbeit selbständig verfasst und keine anderen als die angegebenen Quellen und Hilfsmittel benutzt habe.

Braunschweig, November 2, 2017 _____

Statement of Originality

This thesis has been performed independently with the support of my supervisors. To the best of my knowledge, this thesis contains no material previously published or written by another person except where due reference is made in the text.

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Contents

1 Introduction

Configurable Software Systems. Modern software systems often need to be customized to satisfy user requirements. Configurable software, for instance, enables greater flexibility in supporting varying hardware platforms or tweaking system performance. To make software systems configurable and customizable, they exhibit a variety of *configuration options*, also called *features* (Apel et al., 2013). Configuration options range from fine-grained options that tune small functional- and non-functional properties to those that enable or disable entire parts of the software system. The selection of configuration options can be accommodated at different stages, either at *compile-* or *build-time* when the software is built or at *load-time* before the software is actually used. Compile-time variability usually governs what code sections get compiled in the program. Runtime-variability allows to configure the system during execution, which is needed, for example, for context-sensitive systems. For instance, compile-time variability can be realized by excluding code sections from compilation using preprocessor annotations (Hunsen et al., 2016) or by assembling the code sections to compile incrementally from predefined code modules depending on the feature selection (Schaefer et al., 2010). In contrast to that, load-time variability controls which code sections can be visited during execution. Configurations for load-time variability can be specified using configuration files, environment variables, or command-line arguments. Many software systems are configurable, examples range from small open-source command-line tools to mature ecosystems including Eclipse or even operating systems, such as the Linux kernel with more than 11,000 options (Dietrich et al., 2012).

Configuration options for software systems are usually constrained (e.g., are mutually exclusive, imply or depend on other features) to a certain extent. In the worst case though, at which all options can be selected independently, the number of valid configurations grows exponentially with every feature added, and exceeds the number of atoms in the entire universe once we count 265 independent features. Hence, even for a small number of features, any naive approach for assessing emergent properties of configurable software systems exhaustively for each valid configuration is conceived infeasible. Despite this mathematical limitation, many feasible approaches to static analysis for configurable systems emerged. Those variability-aware approaches enable, for instance, type checking in the presence of variability by exploiting commonalities among different variants (Thüm et al., 2014).

To meet functional and non-functional requirements, users aim at finding the optimal configuration of a configurable software system. However, this task is non-trivial and has shown to be NP-hard (White et al., 2009). The main driver for the complexity are feature interactions. A *feature interaction* is an "emergent behavior that cannot be easily deduced from the behaviors associated with the individual features involved" (Apel et al., 2013) and can make development and maintenance of a configurable system an error-prone task.

To illustrate feature interactions, consider the following example (Siegmund et al., 2015): A software system, say a file server, is used to store files in a database and provide

access upon request. The system provides two features, encryption and compression. In isolation, both file en- or decryption and file (de-)compression demand an expectable fraction of memory and processor time. The performance behavior for the software system though may vary if both features are selected. For instance, if a file is encrypted and compressed (or vice versa), we can expect the operation to demand less resources since an compressed file is likely to be of smaller size than the decompressed original. This is a positive example for a feature interaction, where the performance behavior although being benefitting, is unexpected.

Performance Behavior. The term "performance" with respect to software and software systems is not precisely defined and differs from an end user's and developer's perspective. According to Molyneaux (2014), from a user's perspective "a well-performing application is one that lets the end user carry out a given task without any undue perceived delay or irritation". However, to accurately assess performance, from a practitioner's perspective, performance is outlined by measurements called *key performance indicators* (KPIs) which relate to non-functional requirements (Molyneaux, 2014). The set of KPIs includes availability of a software system, its response time, throughput, and resource utilization. Availability comprises the amount of time an application is available to the user. Response time describes the amount of time it takes to process a task. Throughput describes the program load or number of items passed to a process. Resource utilization describes the used quota of resources required for processing a task.

The performance behavior of a software system depends on the functionality offered, the respective implementation, program load, the underlying hardware system, environment variables, and the resulting execution. Since configuration options control what and how functionality is executed, we concentrate here on this source of performance. While feature interactions not necessarily cause the software system to break severely in all cases, its overall performance can become unfavorable for corner cases or specific configurations as the feature selection influences the execution. That is, the choice of features influences the performance of a software system, too.

Performance and Evolving Software. Actively maintained software systems evolve with every modification made, every version released, and patch provided. Modifications usually introduce new functionality to the system, but functionality might as well be divided into smaller modules to provide more fine-grained configuration options. When features are removed from the software system, the corresponding functionality might remain in the code base or options are merged (Apel et al., 2013).

There exists substantial work on understanding the evolution of configurable systems, for instance, with respect to software architecture (Zhang et al., 2013; Passos et al., 2015) or variability (Seidl et al., 2012; Peng et al., 2011; Passos et al., 2012). As software evolves, the code base which is subject to modifications and the overall architectural quality can degrade. Common symptoms of architectural degradation are code tangling and scattering (Zhang et al., 2013; Passos et al., 2015), which lead to less cohesive and stricter coupled code. The more the code base is constrained and interdependent, the more software can become "brittle" (Perry and Wolf, 1991), less flexible, harder to adapt, and therefore harder to evolve. Evolution of software, especially with respect to variability, is essentially driven by and can be conceived as adapting a software system to changed requirements and contextual changes (Peng et al., 2011). That is, (potential) degradation

of software quality as software evolves is often a phenomenon due to decisions trading quality assurance (QA) and maintenance tasks with meeting requirements and schedules (Guo et al., 2011). The metaphor of *technical debt* (Guo et al., 2011) which is commonly used to describe this trade-offs and corresponding costs, outlines the risk that postponed maintenance tasks pose to software evolution. Although every deferred maintenance or QA task may save some cost, it also could have unveiled software defects in the first place. Technical debt implies both interest, so to speak, the potential damage of a defect depending on its severity, as well as the probability of incurring interest. A defect can be severe, yet fixable with reasonable effort and cost. However, the aforementioned symptoms of architectural degradation and deferring maintenance render bug-fixing to become more and more expensive.

Besides the aspects of software evolution discussed above, the evolution of performance for software systems has gained more attention recently. In practice though, quality assurance with respect to performance is still conducted to an unsatisfactory extent, or accommodated too late in the development process, according to Molyneaux (2014). Thus, postponed maintenance and QA with respect to performance is likely to a driving factor for degradation of performance quality, or simply called *performance regression*.

While performance discipline has emerged as a discipline of or target in software testing, qualitative root-cause analysis, for the most part, is still conducted manually (Molyneaux, 2014). However, there exists work on automated root-cause analysis for performance bugs, such as measuring the execution time of unit tests, whereby an increased execution time indicates performance regression, and the corresponding unit test helps isolating the root-cause thereof (Heger et al., 2013; Nguyen et al., 2014b). In conclusion, we see that, to better assure good software performance, more knowledge about performance behavior needs to be available, ideally, earlier in the development process.

Performance Prediction. For configurable software systems, performance behavior can be more complex and dependent on the feature selection, as we have seen with the example for feature interactions above. Similarly, quality assurance for configurable software systems is far from exhaustively testing all possible configurations, but rather close to only testing a selection of configurations sampled with respect to certain constraints. Sampling strategies might stress feature interactions, such as pair-wise sampling (Siegmund et al., 2012). However, all samples are selected with the intention to learn as much as possible about the entire system from a small sample set of variants. So to speak, a sampling strategy is "optimal" if for a resulting sample set, the probability of missing an arbitrary (relevant) feature interaction, is minimal.

While performance testing is apparently useful, recently, a number of techniques to model and predict performance behavior for arbitrary configurations have emerged (Siegmund et al., 2012, 2015; Guo et al., 2013; Sarkar et al., 2015). The underlying optimization problem of performance-prediction models is to find an accurate estimator $\hat{f}$ for a function f describing a performance property depending on the feature selection. Performance properties can be estimated without performance measurements, for instance by inferring performance properties from software models (Woodside et al., 2007); measurement-based approaches for configurable systems address this optimization problem. The proposed approaches include learning performance behavior with decision trees (Guo et al., 2013; Sarkar et al., 2015), learning a frequency-based representation of the target function (Zhang et al., 2015), or learning the influence of single features and all performance-

relevant feature interactions (Siegmund et al., 2012, 2015). All approaches have shown promising error rates for several real-world applications and allow prediction of system performance for arbitrary configurations. To create performance-prediction models, all approaches demand samples of performance measurements for multiple configurations.

1.1 Problem Statement

The assessment of performance evolution requires a series of performance-prediction models describing performance behavior for a series of versions of a corresponding configurable software system. Assessing the performance behavior for a single version of a configurable software system entails a number of necessary and preliminary tasks. However, these tasks become even more complicated once a series of versions needs to be assessed:

- *Feature Model Synthesis:* Not all configurable software systems do explicitly exhibit a variability model which is, however, required to derive all valid variants (Rabkin and Katz, 2011; Nadi et al., 2015). While substantial work exists on reverse engineering variability models from code (Rabkin and Katz, 2011; She et al., 2011; Zhou et al., 2015; Nadi et al., 2015) or non-code artifacts (Alves et al., 2008; Andersen et al., 2012; Bakar et al., 2015), many techniques still involve manual decisions (She et al., 2011) and domain knowledge (Nadi et al., 2015). Moreover, variability models evolve as part of the software (Peng et al., 2011), vary from version to version, and therefore, require repeated reverse engineering steps.

- *Configuration Translation:* The translation of a valid configuration to a configuration artifact such as a configuration file or a list of command-line arguments usually differs from system to system. This step may be automated, but one still needs to detect how configurations are read by the software system one wants to study.

- *Automated Integration:* The sampe challenge applies to the infrastructure when we need to compile or build a software system for a specific configuration since there exist many possible build tools such as makefiles. Again, the build process can be automated, but one needs to detect and specify the build mechanism used and relate it to a specific configuration.

- *Version-History Sampling:* To study performance evolution,e need to specify which snapshots or versions of a software system are relevant to describe its performance behavior over time. While detecting releases and release candidates should be straightforward, one might, for instance, be interested in the performance evolution including snapshots between two releases, for example after bug fixes. Since it is often the case that not all snapshots do compile, classifying defect snapshots can still be tedious work.

- *Performance Assessment Setup:* The accurate assessment of performance evolution requires a suitable testing setup. The methodology required for assessing performance among others requires the selection of suitable performance metrics and corresponding benchmarks, means to record measurements, and repeat experiments easily as well as proper ways to interpret and compare results.

Goals and Thesis Structure. The goal of this thesis is to provide a theoretical and practical methodology to enable exhaustive performance measurements of configurable software systems and over their version history. That is, we contribute a guideline of and tool support for performance measurements of configurable and evolving software systems. Our research objectives and desired outcomes are

- a literature overview regarding software evolution, feature model synthesis, and performance assessment,
- a methodology to assess performance evolution with respect to the aforementioned challenges, and
- a practical tool for performance measurement for multiple revisions of configurable software systems.

We also propose an approach of automatically detecting promising versions of the configurable software systems for performance measurements and evaluate whether our assumptions hold.

The thesis is organized as follows. Chapter 2 provides the background to the relevant topics discussed in this thesis, including variability modeling, software evolution, feature model synthesis, performance assessment, statistical basics to summarize data records, and performance prediction models. In Chapter **??**, we propose our measurement methodology and discuss the methods used for our performance measurement tool as well as its limitations. In Chapter **??**, we evaluate several aspects of our tool with respect to practicality and discuss the results thereof. Finally, Chapter **??** concludes the thesis and gives an outlook on possible future work.

1.2 A Methodology for Assessing Performance Evolution

The methodology described in this thesis is organized with respect to three dimensions of configurable software systems: variability, version history, and performance. The schematic overview of the performance evolution assessment process shown in Figure 1.1 outlines the major aspects of each dimension.

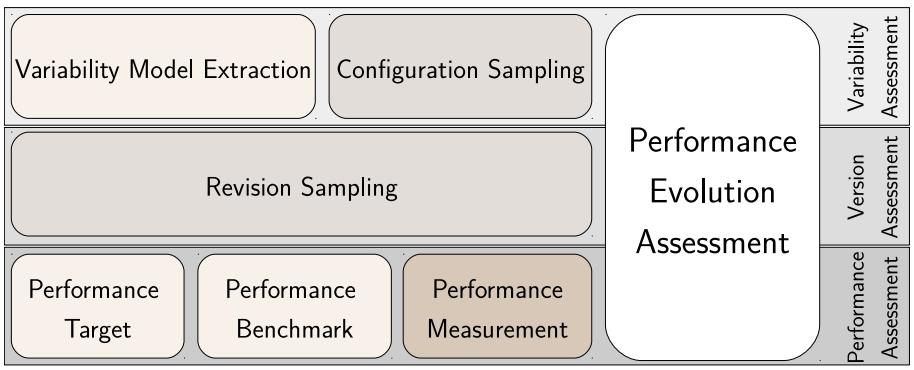


Fig. 1.1. Overview of the the proposed methodology including the necessary processes.

First, objectives related to the variability of a configurable software system are considered. This includes the extraction and comprehension of knowledge about the system's

variability. Second, we address objectives which emerge with evolving software, for instance whether a system compiles for a specific version, or whether a version is a promising candidate for detecting performance changes. Finally, we describe in detail the assessment of performance which comprises the selection of suitable performance benchmarks as well as a selection of appropriate statistical means to summarize, compare, and evaluate performance statistics in order to derive meaningful insights.

In addition to the three aforementioned dimensions in Figure 1.1, performance evolution assessment can also be conceived as consisting of three different categories of tasks, as the different colorizations indicate. First, for a configurable software system, its variability needs to be assessed in order to obtain a variability model to derive and select configurations from. Second, for a software system, a sample set of revisions needs to be selected. Since covering all variants and versions is not feasible, a sampling strategy needs to be chosen which is likely to uncover performance changes. Finally, the performance assessment goals are specified and corresponding measurements are conducted and evaluated as mentioned above.

2 Background

This chapter presents necessary background to the individual topics used in this thesis. In section 2.1, we recapitulate basic concepts, notations, and terminology regarding variability modeling, and section 3.1.2 presents methodologies to recover variability models from source code. In section 2.2, we outline different aspects of software evolution. section 2.3 discusses the assessment and testing of performance and finally, section 2.4 recalls methodology to predict performance behavior for configurable systems.

2.1 Variability Modeling

The design and development of configurable software systems is conceptually divided into *problem space* and *solution space* (Czarnecki and Eisenecker, 2000). The problem space comprises the abstract design of features that are contained in the software system as well as constraints defined among features, such as dependencies or mutual exclusion. The solution space describes the technical realization of features and the functionality described by and associated with features, e.g., implementation and build mechanisms. That is, features cross both spaces since they are mapped to corresponding code artifacts.

A common way to express features and constraints in the problem space is to define a *variability model*, or *feature model*, which subsumes all valid configurations (Kang et al., 1990; Thüm et al., 2009; Apel et al., 2013). There are different and equivalent syntactical approaches to define feature models, for instance, a propositional formula F over the set of features of the configurable software systems (Batory, 2005). In this case, a configuration is valid with respect to the feature model if and only if F holds for all selected features being true and all unselected features being false, respectively. However, a more practical and more commonly used way to express feature models are graphical tree-like *feature diagrams* (Apel et al., 2013). In a feature diagram, features are ordered hierarchically, starting with a root feature and subsequent child features. By definition, the selection of a child feature requires the parent feature to be selected as well. Child features can either be labeled as *optional* features or *mandatory* features; the latter ones need to be selected in every configuration. Moreover, feature diagrams provide a syntax for two different types of feature groups, *or-groups* and *alternative-groups*. For an or-group, at least one of the group's features needs to be selected for a valid configuration, whereas for an alternative-group exactly one out of the group's mutually exclusive features must be selected. In addition to the feature hierarchy, constraints, which cannot be expressed by the tree-like structure, are referred to as *cross-tree constraints*. Cross-tree constraints, depending on the notation, are depicted by arrows between two features or simply added to the feature diagram as a propositional formula. For two features f_1 and f_2, a cross-tree constraint means that for feature f_1 to be selected, either the selection of f_2 is required/implied or excluded.

An introductory example for the syntax and semantics of feature diagrams is provided in Figure 2.1. In this example, an imaginary vehicle propulsion can be configured with

eight valid configurations. The vehicle requires an engine, and therefore feature Engine is mandatory. At least one out of the three features Hybrid, Piston and Electric needs to be selected. For a piston engine, we can select either the feature Diesel or Petrol. A petrol engine requires additional ignition sparks in contrast to a Diesel engine. For an electric engine, we require a battery, hence, the feature Battery is mandatory. In addition, the feature model specifies two cross-tree constraints: First, the feature Tank is optional, yet once a piston engine is selected, we require a tank. Second, if we want to use the Hybrid functionality (e.g., use both electric and piston engine simultaneously), we require to have both a piston and an electric engine.

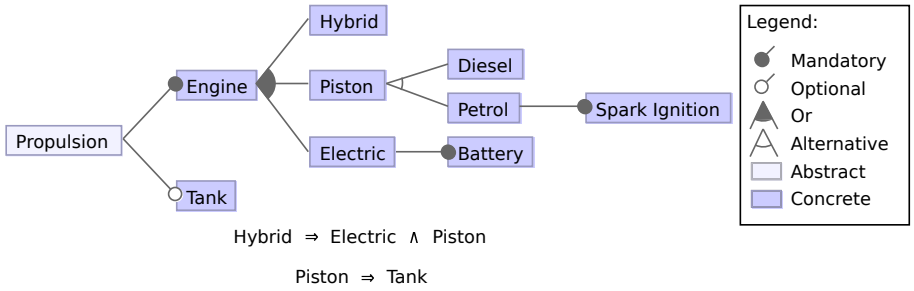


Fig. 2.1. Feature diagram for a feature model with eight valid configurations; two cross-tree constraints are specified as propositional formulas over features

2.2 Software Evolution

The first notion of the software development process is usually developer-centered and merely focuses on software being designed, implemented, tested, and eventually being released and deployed. Maintainability is a generally recognized software quality property to look after, and maintenance is, of course, essential to every successful software system Liggesmeyer (2009). Nonetheless, less attention is given to the ability to adapt a software system to changing requirements (evolvability) rather than maintaining it to keep functionality working (Parnas, 1994). Software evolution and evolvability, such as software itself are manifold. Software evolves in many ways ranging from maintenance (refactoring, bug-fixes, and patches) to adapting to changed requirements (adding, removing, reorganizing functionality, and variability). Modern software systems not only often ship with a variety of configuration options to select from, they also employ routines to be build and sometimes even make use of or are part of platforms, such as apps or plugins. That is, software evolution affects all aforementioned aspects, maintainability as well as evolvability can degrade as software evolves.

2.2.1 Software Erosion

The negative symptoms of software evolution which are referred to as “architectural erosion” (Breivold et al., 2012) have been addressed by many researchers. Most of existing research so far though focuses on evolution with regard to software architecture (Breivold et al., 2012). The main driving factors leading to symptoms of decay identified by Perry and Wolf (1991) are architectural erosion and architectural drift. While architectural drift subsumes developers’ insensitivity when not following a systems architecture or respective

guidelines while making changes, architectural erosion subsumes ignoring and violating the existing software architecture. Parnas (1994) argues that as software evolves, software is maintained and evolved by developers who are not necessarily familiar with the initial architectural design. Therefore, knowledge about the architecture can become unavailable as software evolves. Although the unfavorable effects of software evolution do not break a system necessarily and imminently, the software becomes "brittle" (Perry and Wolf, 1991) as maintainability as well as evolvability degrade. Concrete symptoms of software erosion on the implementation level have been documented.

Zhang et al. (2013) have studied erosion symptoms for a large-scale industrial software product line with compile-time variability using preprocessor directives. The authors identify variability-related directives and clusters of those that tend to become more complex as the software evolves. The negative effects, or symptoms of software erosion are described as, but not limited to *code replication* and inter-dependencies between code elements, such as *scattering* and *tangling*. Code scattering describes the phenomenon of code belonging to a certain feature being scattered across multiple units of implementation, such as modules, whereas code tangling means that code from different and potentially unrelated features in entangled within a single module.

Passos et al. (2015) have studied the extent of usage of scattering for device-drivers in the Linux kernel. Despite scattering being quite prevalent, their findings suggest that the kernel architecture is robust enough to have evolved successfully. Nonetheless, platform drivers in the Linux kernel seem more likely to be scattered than non-platform drivers. They conclude that this is a trade-off between maintainability and performance: a more generalized and abstract implementation for platform-drivers in this case could possibly avoid scattering, yet refactorings in this manner did not seem to be necessary or worth the effort yet.

2.2.2 Variability Evolution

Apart from architecture evolution, the variability offered by software systems evolves as well. For configurable software systems, evolution steps will not only affect artifacts in the solution space, yet also be visible in changes in the respective variability models in the problem space. Although the variability aspect of software evolution has not gathered as much attention as architecture in the past, more and more research has emerged recently to address and understand variability evolution.

Peng et al. (2011) proposed a classification of variability evolution patterns that conceives evolution as adaption to changing (non-)functional requirements and contexts. For a context in that sense, two categories exist. A driving context determines, whether a variability model and respective variants can meet functional requirements in the first place. A supporting context by definition determines how non-functional properties are strengthened or weakened. Any changed requirement is likely to change the contexts for a software systems variability model and, therefore, will make adaptations of the variability model necessary. Within their classification method, Peng et al. (2011) identify major causes for variability evolution, comprising (a) new driving contexts emerging, (b) weakened supporting contexts (for instance, due to new non-functional requirements), and (c) unfavorable trade-offs for non-functional properties.

To understand single evolutionary steps, several catalogs of variability evolution patterns have been proposed. Peng et al. (2011) present three patterns, where either a new

feature is added, a mandatory feature becomes optional, or a mandatory/optional feature is split into alternative features. Seidl et al. (2012) suggest a catalog of patterns for co-evolution of variability models and feature mappings that additionally introduces code clones, splitting a feature into more fine-grained sub-features, and feature removal as evolution patterns. In addition, Passos et al. (2012) have studied variability evolution in the Linux kernel and present a catalog of patterns where features are removed from the variability model, but remain a part of the implementation. Their catalog, among others, includes feature merges, either implicit (optional feature merged with its parent) or explicit.

The classification proposed by Peng et al. (2011) is a general and formalized approach that, as well as Seidl et al. (2012) and Passos et al. (2012), describes elementary evolution patterns which can be composed to more complex patterns. Nonetheless, no comprehensive catalog of variability evolution patterns so far has been proposed.

2.3 Assessing Performance

While the last three sections covered software evolution and variability modeling, we now step forward to the topic of software performance. This section will outline the term performance with respect to software systems as well as to possible measurements. We provide a brief look at the general performance testing setup and the required prerequisites, including suitable benchmarks. Finally, we provide the statistical background to summarize, interpret and compare performance measurements accurately.

2.3.1 What is Performance?

The performance of software systems is, like software quality, primarily a matter of perspective. While an end user might consider practical aspects to be more important, from a developer's perspective, performance relates to and is best described by non-functional properties (Liggesmeyer, 2009; Molyneaux, 2014). While functional properties subsume what exactly a software system does, non-functional properties describe how (good or bad) a software system is at providing the functionality offered (Liggesmeyer, 2009). The notion of good and bad in this sense corresponds to non-functional requirements (NFR), that is, software with "good" performance behavior does not violate its NFRs. The categories of NFRs that shape performance behavior are manifold. According to Molyneaux (2014), the categories or *key performance indicators* (KPIs) include

- availability
- response time,
- throughput,
- resource utilization, and in a broader scope also
- capacity.

Time-related KPIs are availability and response time, whereby availability describes the time or time ratio that the software is available to the end user, and response time

subsumes the time it takes to finish a request or operation. Throughput as a category subsumes the program behavior with respect to program load, such as hits per second for a Web application or amount of data processed per second. Resource utilization describes the extent to which a software system uses the physical resources (CPU time, memory, and disk, or cache space) of the host machine. Finally, from a Web-centered perspective, capacity describes measurements with respect to servers and networks, such as network utilization (traffic, transmission rate) and server utilization, such as resource limitations per application on a host server (Molyneaux, 2014).

Consequently, the assessment of performance requires a context or testing target that corresponds to the assessed system under test (SUT). For instance, for a simple command-line compression tool, suitable KPIs are response time and throughput, whereas performance for an online shop Web application is better outlined by availability and capacity.

2.3.2 Performance Testing

The first step in performance testing, prior to defining relevant KPIs and metrics, is to specify a system operation or *use case* (Woodside et al., 2007) to assess performance for. A typical use case includes a well defined task or workload to process, expected behavior, outcome, and performance requirements as previously discussed. For the SUT, however, we require a version that does compile or, in case it is interpreted, is syntactically correct (Molyneaux, 2014). With regard to performance assessments as part of the development process, a code freeze should be obtained since measurement results are likely to become meaningless for later versions. In addition to that, the machine or setup used for performance measurement should ideally be as close to the production environment as possible, but at least be documented to compare different runs (Molyneaux, 2014).

Finally, one or more benchmarks need to be selected to simulate the program load for the respective use case. A benchmark, all in all, needs to be representative, i.e., should relate to the use case or requirement one wants to validate. While benchmarks for file compression usually include multiple different types of media data (text, sound, pictures) such as the Canterbury corpus[1], Web applications can be exposed to handling with a number of simulated users at the same time (Molyneaux, 2014). Benchmarks have often been standardized within research and engineering communities to provide comparable performance measurements. A popular example is the Software Performance Evaluation Corporation (SPEC), a consortium providing a variety of benchmarks such as the CPU2000[2] processor benchmark consisting of programs with both floating point and integer operations. Moreover, benchmarks, in a sense of repeatable program load, can be obtained from load generation software such as ApacheBench[3] for the Apache Web server or simply by measuring performance for test cases (Heger et al., 2013; Nguyen et al., 2014b).

Performance testing heavily relies on tool support, especially for repeating test cases and recording measurements. Since the tool solutions for performance testing vary from domain, scale, and purpose, we will outline only the general tool architecture. Molyneaux (2014) describes four primary components for a performance testing setup: a scripting module, a test management module, a load injector, and an analysis module. A scripting

[1]The Canterbury corpus can be found here, `http://corpus.canterbury.ac.nz/`.
[2]The benchmark description can be found at `https://www.spec.org/cpu2000/`.
[3]Manual page of the Apache tool `ab`, `http://httpd.apache.org/docs/2.4/en/programs/ab.html`.

module handles the generation or repetition of use cases which, for instance, can be recorded prior to the test for Web applications. A test management module creates and executes a test session, whose program load is generated by one or more load injectors. A load injector can provide a benchmark by generating items to process, or can simulate a number of clients for a server-side application. An analysis module, finally, collects and summarizes data related to the performance testing target. We present more on summarizing and comparing recorded results in the Section **??**.

2.4 Performance Prediction Models

In the previous section, we referred to performance, or in detail, the KPIs, as possible testing targets, which we validate against non-functional requirements. However, in a broader sense, software performance has become an aspect of software engineering referred to as *software performance engineering* (SPE) (Woodside et al., 2007). A lot of effort has been spent to study and describe performance behavior as well as to improve performance quality. Besides the analysis of concerns or requirements with respect to performance, SPE comprises performance testing as well as performance prediction (Woodside et al., 2007). Performance prediction aims at modeling and estimating performance behavior for different use cases or configurations. The first approaches to performance prediction models describe the underlying software system component or operation from which performance estimations are then deduced. These so-called *model-based prediction models* enable a performance estimation early in the development process since no actual performance measurement is required (Woodside et al., 2007). In contrast to model-based approaches, measurement-based approaches have emerged. These *measurement-based prediction models* are based on a sample of performance measures which are used to learn a software system's performance behavior (Woodside et al., 2007). More recently, measurement-based prediction models that emphasize variability have been proposed, of which we will discuss three approaches in the remainder of this section.

Learning Performance In essence, learning and predicting performance behavior for a configurable system means nothing different than finding an approximation $\hat{f}$ for a function $f : C \to \mathbb{R}$ where C is the set of configurations and $f(c) \in \mathbb{R}$ with $c \in C$ is the corresponding performance measurement. The accuracy of the approximation $\hat{f}$ describes how the estimated performance $\hat{f}(c)$ deviates from the actually measured performance $f(c)$. Different approaches to construct such an approximation, referred to as a *performance prediction model*, emerged recently. All approaches utilize two samples of configurations and corresponding performance measurements to build and validate the model. A training sample is used to learn the approximation from, whereas a testing sample is used to assess the prediction error rate of the previously learned approximation.

A straightforward methodology to learn performance behavior was proposed by (Guo et al., 2013). The authors utilize classification-and-regression-trees (CART), akin to decision trees, to derive a top-down classification hierarchy for a given sample. The approach supports progressive (and random) sampling, i.e., the performance model is constructed several times while the size of the training sample is successively increased. The CART is constructed by recursively partitioning the sample into smaller segments which best describe a class. It is worth mentioning that the estimation using CART is not limited

to binary configuration options, but supports numeric features as well. Moreover, the approach by (Guo et al., 2013) does not produce any further computation overhead besides the measurement effort and the construction of a CART.

A different approach to modeling performance behavior was proposed by Zhang et al. (2015). The authors propose an approach to construct performance prediction models based on a Fourier description of the performance-describing function f, which maps each configuration to a corresponding performance measurement. The principal idea is to approximate a Fourier series approximating the function f, and learning all coefficients of the Forier series terms.

The number of terms is exponential in the number of configuration options. The main characteristic of this approach is that, prior to learning a performance prediction model, a desired level of prediction accuracy can be specified. That is, the approach automatically chooses the sample size required to learn the prediction model accordingly.

A third approach to model and predict performance behavior, *SPLConqueror*, was proposed by Siegmund et al. (2012). The authors describe performance behavior for a configuration as the accumulated influence of features, from which the configuration is composed, and respective feature interactions. To estimate the influence of single features and feature interactions, the authors propose a number of sampling strategies. Single features are assessed by comparing the performance of two different configurations per feature: For a feature f, two valid configurations are compared, whereby both configurations have the minimal number of features selected that are not excluded by the selection of f. While for one configuration f is selected, it is deselected for the other one. The difference between the performance measures for both configurations is the estimate $\Delta_{min(f)}$ for the performance influence of feature f. Feature interactions that are performance-relevant are detected automatically in a similar manner. The main idea is, that a feature f is more likely to interact with other features, the more features are selected along with f. Therefore, if f interacts, the influence of feature f, $\Delta_{min(f)}$ differs from the influence of f, when estimated using configurations where the maximal number of features selectable together with f are used. Based on the set of interacting features, three heuristics are employed to detect feature interactions. Simple feature interactions are detected using pair-wise sampling (Siegmund et al., 2012; Apel et al., 2013), whereas higher-order feature interactions are often composed from simpler ones, or centered around a small subset of hot-spot features (Siegmund et al., 2012). Finally, for an arbitrary configuration, the performance can be predicted by the sum of influence estimations per feature and feature interaction.

The idea of predicting performance by estimating the influence of feature and feature interactions was further developed by Siegmund et al. (2015) by proposing performance-influence models for both binary and numeric configuration options. A performance influence, similar to *SPLConqueror*, predicts performance by computing the sum of previously learned influence estimates. The novelty of this approach lies in the way the terms describing the influence of feature and feature interactions are learned and not derived from a sampling strategy. Instead of a single constant performance influence estimate, each term can contain of a number of functions, such as linear, quadratic, or logarithm functions, or compositions thereof. This does not only allow the developer to incorporate domain knowledge by preselecting functions. Moreover, but also by introducing combinations of non-linear functions and learning the coefficients using linear regressions, it enables learning a non-linear function. The algorithm commences with the selection of terms and

successively extends and reduces the term selection to increase the prediction accuracy. The outcome, similar to Siegmund et al. (2012), is a linear function whose terms represent the estimated influence of features and feature interactions on performance.

All aforementioned approaches rely on performance measurements and, to some extent, also on a sampling strategy. While the approaches by Siegmund et al. (2012, 2015) essentially describe sampling strategies, the approach proposed by Zhang et al. (2015) is able to work with random samples, and the approach of Guo et al. (2013) allows a smaller sample to be extended progressively (Guo et al., 2013). As performance measurements entails an expensive and time-consuming process, Sarkar et al. (2015) have investigated different sampling strategies in this domain. The authors compare progressive sampling, where sample sizes are increased successively until the learned prediction model performs accurately enough, and projective sampling, where the optimal sample size is estimated based on the expected learning curve, with respect to cost and prediction accuracy. They advocate the use of projective sampling over progressive sampling. In addition, the authors propose and evaluate an own sampling heuristic to select an initial sample for progressive sampling. This sampling heuristic is based on feature frequencies and outperforms t-wise sampling, such as pair-wise sampling (Sarkar et al., 2015).

3 Methodology: Variability Assessment

To assess performance evolution for configurable software systems, it is required to assess and understand variability of such systems with respect to various aspects: *First*, to actually assess single variants, knowledge about the variability model is required to configure the software systems accordingly. *Second*, obtaining knowledge about feature usage and implementation can provide meaningful insights. For instance, knowing that most variable code is dependent on small numbers of features might be useful information when selecting a sampling strategy. Similarly, knowing which feature combinations are frequently involved in conditioning program functionality and behavior can help understand configuration-related defects. *Last*, since the number of configurations for most configurable software systems is infeasible, variability assessment faces performance- and scalability-related problems. That is, variability assessment is usually constrained by limited resources.

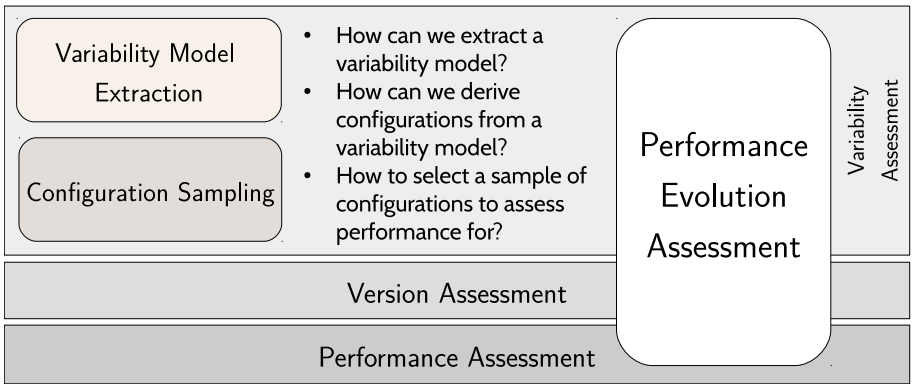


Fig. 3.1. Methodological roadmap: questions to address during variability assessment.

This chapter describes the first aspect in our methodology, the assessment of variability. As illustrated in Figure 3.1, this first tier of our methodology embraces two main tasks, first, the synthesis (or extraction) of a variability model for a configurable software system, and second, strategies to select meaningful sample sets of configurations to assess performance for. In section 3.1 we review the synthesis of variability models as well as corresponding analyses of systems' variability; in section 3.2 we describe means to generate configurations from variability models, and finally, section 3.3 discusses different strategies for selecting sample sets of configurations.

3.1 Untangling Variability

Before presenting strategies to synthesize variability models in the next section, we first recap a number of techniques to untangle configurable software composed from variable and invariant code. In the context of our methodology, these techniques are useful means

to make variable code segments visible, and to understand how variability influences the overall resulting variants of a software systems.

The idea of designing and developing configurable software systems is driven by the separation of different concerns, expressed as features of a software system. A configurable software system is either assembled at compile-time with respect to its configuration, or tailored to a configuration at load-time. Both ways of implementing the variability exist in practice. Research has also proposed a variety of variant-generating implementation techniques for compile-time variability, ranging from simple preprocessor directives to features as separate modules (Kästner et al., 2009). A complete survey of means to implement configurable software systems would likely exceed the scope of this section, yet we intend to discuss in this section which information regarding variability is required or useful to our methodology, and how it can be obtained.

3.1.1 Family-based Analyses

As the number of variants for configurable software systems is usually infeasible, naive analyses of configurable systems are not trivial. Any static analysis can only assess one variant at a time, as well as dynamic analyses, which can follow only one execution path. In contrast to that, recently, extended analysis techniques, which are aware of variability of the systems studied, have emerged (Thüm et al., 2014). In particular, these *family-based* analyses avoid redundant computation, such as visiting a code section multiple times, and exploit artifacts shared by multiple variants (Thüm et al., 2014). Besides more efficient analysis, family-based methods incorporate knowledge about valid feature combinations (Thüm et al., 2014) and, therefore, connect analysis results with a context, such as feature combinations, for which the findings hold. Family-based methods have been widely used across various domains and can provide useful information when assessing configurable software systems.

Variability-aware Parsing. Kästner et al. (2011) have proposed the framework *TypeChef* to enable the construction of variability-aware parsers. A variability-aware parser, like ordinary parsers, systematically explores a program to return an abstract representation of the parsed program. This parse tree, or abstract syntax tree, is the basis for compilers to translate a program, or for further static analyses, such as type checking. For a code base with variability expressed by preprocessor annotations, which are evaluated prior to compilation, a variability-aware parser, however, is able to derive a parse tree considering all variants in a single run. A parse tree usually consists of nodes representing syntactical features of the parsed program. The parse tree returned by a variability-aware parser, moreover, comprehends variable segments of a program and will include them with respect to their presence conditions. For instance, a class may contain a function *sort()*, for which two different implementations exist. While there might be numerous variants, the parse tree of the class will contain a node with two children, one for each implementation; higher numbers of alternative implementations are expressed by nesting further nodes. In that way, variable and invariant program segments can be separated.

While the approach of Kästner et al. (2011) handles undisciplined usage of preprocessor directives, such as splitting function parameter lists, variable types, or expressions, Medeiros et al. (2017) have proposed an approach to avoid and conservatively refactor those cases. The authors propose a catalog of refactoring templates, which describe trans-

formations from undisciplined usage of preprocessor annotations to disciplined ones. With respect to variability-aware parsing, disciplined usage is conceived as using preprocessor annotations only to segment statements, but not to segment a single syntactical unit, such as expressions (Medeiros et al., 2017).

In the context of our methodology, the parse tree resulting from variability-aware parsing can be used as a basis for further analyses. Since the parse tree provides a machine-readable decomposition of variable and invariant code segments along with presence conditions, for instance, it has been used to derive constraints among features (Nadi et al., 2014, 2015) as we will see in the next subsection.

Staged Variability. Besides variability-aware parsing, Nguyen et al. (2014a) have applied symbolic execution (King, 1976; Darringer and King, 1978) to unwind variability for PHP Web applications. Web applications are staged, i.e., even though they can be configured at load-time, the application is as well variable with respect to input received at run-time. For instance, consider *WordPress*, a popular content management system (CMS) implemented in PHP, which can be extended with a number of plug-ins. However, the content of a website presented to the user also depends on information retrieved from a database, and user input. Consequently, a dynamic PHP Web application is staged in a sense that it generates configurable HTML templates which are rendered at run-time. The authors utilize a symbolic execution engine to explore all possible execution paths. Each user input or database query is considered a symbolic value which is propagated through each script. By keeping track of the (partially symbolic) HTML output and organizing it in a DOM-like structure, their approach approximates the HTML output, which subsequently can be tested, for instance for validity (Nguyen et al., 2011). Similarly, Lillack et al. (2014) have applied taint-analysis to configurable software systems to track the influence of configuration options read at load-time. Their static analysis approach taints every value resulting from reading a configuration parameter as well as every value resulting from a computation that involves previously tainted values. That way, lines of code that are possibly depending on configuration options are detected.

In the context of our methodology, addressing staged variability with techniques such as symbolic execution is required to assess performance for Web applications. Both the code executed at server-side as well as the dynamically generated HTML are interdependent parts of the Web application. Any suitable and elaborate performance measurement setup for Web applications must incorporate both stages.

Build System Variability. Apart from configuring software systems using preprocessor annotations, the assembling of a configurable software system can as well be orchestrated by its underlying build system. While preprocessor annotations virtually separate code fragments of different features, for instance, build systems can physically exclude files from compilation. This implementation of variability enabled by build systems, in particular of Makefiles, has been subject to a couple of analysis approaches. Tamrawi et al. (2012) have proposed *Symake*, a symbolic execution engine to evaluate Makefiles. On top of *Symake*, Zhou et al. (2015) utilize symbolic execution to analyze Makefiles and derive file presence conditions, stating under which feature selection a file is included or excluded from compilation. The work of Al-Kofahi et al. (2016) addresses a more advanced build system, *GNU Automake*. *Automake* describes a staged build process, where a Makefile can be specified on a higher level, and is subsequently compiled to an actual Makefile.

The authors' aim to provide a variability-aware representation of all possible Makefiles to enable further analyses of the build process.

In the context of out methodology, the symbolic evaluation of a software system's build process follows an intention similar to the one of variability-aware parsing. Not only could further analysis tools be build upon a symbolic evaluation engine, but also does symbolic evaluation in this context untangle the variability accommodated in the build process. The file presence conditions extracted by Zhou et al. (2015) and Al-Kofahi et al. (2016) are a strong basis for further constraint extraction, and therefore variability model assessment.

In the context of our methodology, the mentioned family-based analyses serve two fundamental purposes. *First*, family-based analyses can help to obtain an overview of what, or how much code in a configurable software system is variable as well as to which extent. For instance, if most extracted presence conditions contain only very few features, higher-order feature interactions are unlikely. *Second*, family-based analyses provide a feasible means to untangle variability and, as we will see in the next section, are the basis for some elaborate techniques to extract variability models (Nadi et al., 2014, 2015). In conclusion, these analyses are not essential to extract variability models, yet are useful tools to use in addition to the strategies mentioned in the next section.

3.1.2 Variability Model Synthesis

A variability model as an abstraction of functionality of a software system is required, or at least of great interest, in many contexts. Not every configurable system provides an explicit representation of its variability model. The reasons for inexplicit or absent configuration specification are manifold. They can range from poor or inconsistent documentation (Rabkin and Katz, 2011) to overly complex configurability (Xu et al., 2015), or configuration constraints originated in different layers of a software system, such as build constraints or compiler constraints (Nadi et al., 2014, 2015). The following paragraphs review different *strategies to synthesize variability models* from different types of artifacts. A classification of strategies, along with corresponding literature is illustrated in Figure 3.2 The first category comprises extraction based on Natural Language Processing (NLP) utilize similarities between textual representations of different variants to derive common features (Alves et al., 2008; Bakar et al., 2015). The approaches in the second category are heuristics based on static analyses, whereby configuration option names (Rabkin and Katz, 2011) are extracted, or constraints are derived from assessing the software's build process (Nadi et al., 2014, 2015). The last category comprises techniques which conceive variability model as an optimization problem. For a set of given and valid configurations, genetic algorithms are used to approximate an optimal feature model representing constraints among features (Lopez-Herrejon et al., 2012, 2015; Linsbauer et al., 2014).

NLP-based Extraction. As feature diagrams group and organize features (representing functionality), synthesizing a variability model has shown to be applicable to extract features and constraints from natural language artifacts. For instance, by comparing product specifications for an existing market domain, variability models can provide a detailed feature summary (Alves et al., 2008).

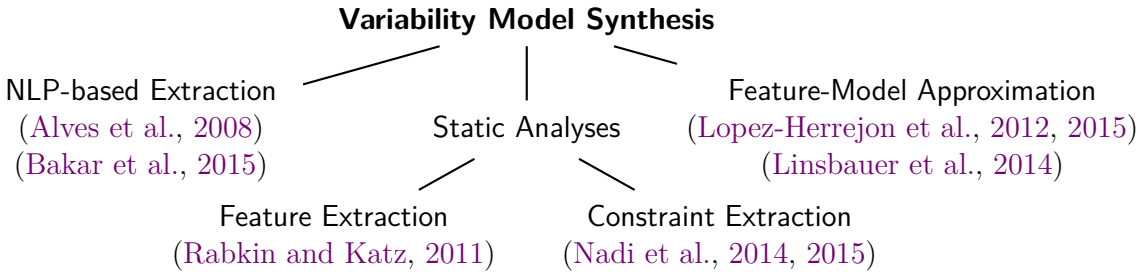


Fig. 3.2. Overview of our literature survey on variability model synthesis.

The basic idea is to identify commonalities and differences in natural language documents, such as product descriptions, requirements, or documentations, by using natural language processing (NLP) techniques (Bakar et al., 2015). A widely employed technique is to conceive a text as a vector in a vector space model, where each word or token represents a dimension. From the tokenized text, irrelevant stop words are removed, and all remaining words are reduced to their original word stems. The importance of all remaining tokens is (usually) weighed by its tf-idf value, an established technique in information retrieval. That is, each text (corresponding to a variant or configuration) is represented as a vector of tf-idf values in the aforementioned vector space model. Based on these representations, text instances are clustered to identify commonalities and differences, for instance in terms of shared words. Subsequently, the clustering information can be used to extract features or entire feature models (Alves et al., 2008; Bakar et al., 2015).

Feature Extraction. Rabkin and Katz (2011) proposed a static, yet heuristic approach to extract configuration options along with respective types and domains. Their approach exploits the usage of configuration APIs and works in two stages. It commences with extracting all code sections where configuration options are parsed. Next, configuration names can be recovered as they are either already specified at compile-time or can be reconstructed using string analysis yielding respective regular expressions. Moreover, the authors employ a number of heuristics to infer the type of parsed options as well as respective domains. *First*, the return type of the parsing method is likely to indicate the type of the configuration option read. *Second*, if a string value is read initially, the library method it is passed to can reveal valuable information about the actual type. For instance, a method `parseInteger` is likely to parse an integer value. *Third*, whenever a parsed configuration option is compared against a constant, expression, or value of an enum class, these might indicate valid values or at least corner cases of the configuration option domain. The extraction method by Rabkin and Katz (2011) is precise, but limited, for instance, when an option leaves the scope of the source code and is passed to a database. Nonetheless, for the systems studied, the authors were able to recover configuration options that were not documented, only used for debugging or even not used at all.

Constraint Extraction. A more comprehensive investigation of configuration constraints and their origin is provided by Nadi et al. (2014, 2015). They use variability-aware parsing to infer constraints by evaluating Makefiles and analyzing preprocessor directives. Inferred constraints result from violations of two assumed rules, where (a) every valid configuration

must not contain build-time errors and (b) every valid configuration should result in a lexically different program. While the first rule aims at inferring constraints that prevent build-time errors, the second one is intended to detect features without any effect, at least as part of some configurations. Their analysis has shown a high accuracy in recovering constraints with 93 % for constraints inferred by the first rule and 77 % for second one respectively. However, their approach recovered only 28 % of all constraints present in the software system. Further qualitative investigation, including developer interviews, lead to the conclusion that most of existing constraints stem from domain knowledge (Nadi et al., 2015).

Feature-Model Approximation. A different strategy to recover variability models, instead of analyzing the software artifacts, is to approximate a model. Given a selection of valid feature selections, a variability model best describing the configurations can be approximated, or learned. Lopez-Herrejon et al. (2015) have surveyed different search-based strategies to synthesize feature models of which we present two categories. Evolutionary algorithms have been applied to reverse engineer feature models from configuration samples (Lopez-Herrejon et al., 2012; Linsbauer et al., 2014). A population of feature models is generated and each instance is evaluated by a fitness function, measuring how well it fits the given sample set of configurations. Subsequently, a new generation is obtained by applying crossover and mutation operators to the previous generation, whereby only the fittest instances remain. This process of evolution is repeated multiple times until a desired threshold fitness is reached for a feature model instance. Lopez-Herrejon et al. (2012) identify a trade-off between the accuracy of recovered feature models and the number of generations employed by evolutionary algorithms. Besides promising results, the authors stress the importance of effective and scalable fitness functions as well as meaningful samples to learn the feature model from. Contrary to evolutionary algorithms, Haslinger et al. (2011, 2013) have proposed an ad-hoc algorithm to reverse engineer feature models. The algorithm recovers the feature model layer by layer via extracting all child features for a given parent feature recursively. The algorithm does not consider cross-tree constraints. Besides promising results for basic feature models, the authors advocate the incorporation of human domain-knowledge in the synthesis of feature models.

Feature-Hierarchy Recovery. Besides recovering features and their respective constraints, to reverse engineer a feature model, one further step is required when the outcome should be human readable in a feature diagram. The recovered knowledge can be organized in a tree-like hierarchy with feature groups specified and cross-tree constraints explicitly stated to derive a valid feature diagram (Kang et al., 1990). While several approaches for recovering the feature-model hierarchy have been proposed, we are primarily interested in finding a hierarchy for knowledge obtained from source code. In the remainder of this subsection, we will focus on organizing features and constraints extracted from source code.

Given an extracted set of features along with corresponding descriptions and recovered constraints among the features, She et al. (2011) propose a semi-automated and interactive approach to synthesize a feature hierarchy. Their approach comprises three steps. *First*, an overall feature hierarchy based on feature implications is specified. *Second*, potential feature groups are detected and manually selected. *Finally*, the feature diagram is extended with remaining CTCs. The approach by She et al. (2011) provides a practical

algorithm to synthesize a feature diagram, yet has some limitations we need to consider. *First*, the approach is not able to detect or-groups as defined in Sec. 2.1. *Second*, the approach does introduce a root feature. *Finally*, the approach does not distinguish between mandatory and optional features. Implicitly, all features that do not have a parent feature are optional and all features that have a parent feature are by default mandatory. She et al. (2011) evaluated the algorithm with both complete and incomplete variability knowledge (feature names, descriptions and constraints). While the algorithm has shown to be practical, detecting features whose parent was the root-feature was difficult since, due to the transitive property of implication, it is implied by each feature of the feature model.

Although the approaches mentioned in the paragraphs above, excluding the feature-hierarchy recovery, in principal address the same problem, they are isolated solutions to the problem of variability assessment, and their applicability is depending on a number of cross-cutting boundary conditions. *First*, for the overall problem of variability model synthesis we can identify two different contexts for which different techniques apply. The NLP-based techniques summarized by Alves et al. (2008) and Bakar et al. (2015) address the extraction of features in the context of requirements engineering, for instance by comparing different software products in the same market domain. However, the remaining techniques intend to extract features for a given single software system. *Second*, for variability assessment there exist two different principal analysis approaches. While the techniques proposed by Nadi et al. (2014, 2015) and Rabkin and Katz (2011) approach a configurable software system as a monolithic system, both the family of NLP-based techniques and the approximative techniques Lopez-Herrejon et al. (2012, 2015); Linsbauer et al. (2014) explicitly require a set of variants or configurations, respectively. *Third*, the techniques differ in the type of variability they are able to extract variability models for. While Nadi's approach only works for build-time variability, the work of Rabkin and Katz (2011) will only work for configurations read at load-time. Moreover, the remaining techniques do not consider the different types of variability at all.

In conclusion, it becomes clear that there is no single textbook solution to the problem of variability model assessment as this problem may arise in different contexts be approached from different perspectives, or be emergent for different types of variability.

3.1.3 Methodological Strategies

The last two subsections reviewed a number of family-based analyses for configurable software systems as well as approaches proposed to partially extract variability models from a system's code base. The latter approaches presented, however, are rather isolated solutions due to non-generic assumptions, such as the use of configuration APIs (Rabkin and Katz, 2011), or build-time variability (Nadi et al., 2015). At best, these approaches complement each other, or are an appropriate choice under certain circumstances, still requiring further manual assessment. The following integrates the previously discussed work and proposes methodological strategies to synthesize variability models for different scenarios, or use cases.

For the recovery of variability models, we propose three scenarios. Clearly, this is not an exhaustive list, but covers the majority of use cases based on our literature review. The scenarios should provide a practical context to the previously mentioned techniques. The

Criterion	Scenario A	Scenario B	Scenario C
Configurability documentated?	√	(√)	(√)
Configurations provided?	×	√	(√)
Variability model provided?	×	×	√

√ = Criterion satisfied, (√) = Criterion satisfied optionally, × = Criterion not satisfied

Tab. 3.1. Distinction of three scenarios for variability model synthesis.

three scenarios are outlined in Table 3.1; we derive our scenarios based on three criteria. *First*, we ask whether, and if so, to what extent configurability for a software system is documented. *Second*, we ask whether the software system provides sample configurations, such as configuration presets, or whether it ships as different variants, such as different Windows flavors. *Last*, we ask whether a variability model is explicitly contained in the software, and whether it is visible to practitioners, such as the *Kconfig* system for the Linux kernel. For each scenario, in Table 3.1, satisfaction of either criterion is marked. In addition, we mark criteria as *satisfied optionally*, if we assume them to be satisfied, but they are not necessarily relevant for the choice of strategy.

Apparently, the latter scenario C in Table 3.1 requires only little to no assessment of the application's variability since the variability model is already available.

For scenario B, despite documentation might be available, the previously presented variability model approximation approaches (Haslinger et al., 2011, 2013; Lopez-Herrejon et al., 2012; Linsbauer et al., 2014) can be applied, yet only binary configuration options are supported so far. Given the existence of sample configuration or configuration presets, these may provide additional information to answer the questions stated above. The remaining approaches mentioned in the previous subsections, unfortunately, describe only isolated solutions. Given suitable circumstances, they can nevertheless aid the extraction of variability models. The overall scheme in synthesizing a variability model is to answer the the questions above manually, and refer to automated tool support whenever possible.

For scenario A, when the main source of information regarding variability is the software system's documentation, we are left with no other option than manual assessment. To do so, we provide a questionnaire of five main questions to be anwered in Table 3.2. The corners of the questionnaire cover, besides the manual synthesis of the variability model, the questions of how variability is implemented, configurations are encoded, and whether the variability model has changed during evolution. Although the automated approaches discusses earlier are only applicable for scenarios B or C, or under specific circumstances, family-based analyses can support manual assessment.

We have seen that the extent to which automated solutions are applicable to variability assessment depends on the degree to which variability is documented. If the variability model is available in a machine-readable format, little to no further assessment is required, while, if documentation was done manually, so variability assessment remains a task to be done manually. In conclusion, the questionnaire in Table 3.2 covers most aspects required to comprehend variability for a configurable software system and can be conceived as a guideline. Whenever applicable, additional synthesis or analysis techniques can be taken into account.

Question	What approach or technique to use?	Information Gain
How is variability implemented? *Variability can be accommodated at build- or load-time.*	□ Manual review of the documentation with respect to what configuration mechanism is used, such as run-time parameters or preprocessor annotations. □ Family-based variability analyses help understand what parts of the software are variable and how they are enabled, or made accessible.	Knowledge of whether the software must be compiled for each configuration, or only for each version.
How can the software be configured? *Variability can be implemented in various ways.*	□ Manual review of the documentation with respect to how configurations are actually encoded to be machine-readable. Look out for standard or example configurations.	Knowledge about how a configuration can be translated to a machine-readable format required by the software, such as argument lists or preprocessor annotations.
Which configuration options exist, including types and domains? *Configuration options can be binary or numeric options.*	□ List all configuration options mentioned in the documentation. Unless not provided, consider standard or sample configurations or option names to infer a type, and valid values and corresponding domains.	Knowledge about what configuration options exist, whether they are binary or numeric options, and what valid values can be assigned to them.
Which dependencies or exist between and among configuration options?	□ Manual review of the configuration options with respect to implied, excluded, or alternative configuration options. Similarly, numeric constraints may exist.	Obtaining a (approximated) variability model, which is required to decide whether a configuration is valid or not.
Has the feature model been changed during evolution?	□ Review of release notes and changes in the documentation with respect to new features as well as constraints added, modified, or removed. □ Manual inspection of changes over time in code sections where configuration options are read.	Knowledge about whether synthesizing different versions of the variability model is required.

Tab. 3.2. Questionnaire for manual variability assessment.

3.2 Configuration Generation

The next intermediate step in our methodology is the generation of configurations from the variability model. Once obtained, we use the variability model to derive valid feature selections. For the assessment of quality attributes for configurable software systems, such as test case coverage or performance, we usually assess a sample set of variants. Hence, we require techniques to derive valid feature selections from the variability model to select meaningful sample sets from. As there exist various forms to express a variability model, configurations may be generated in various ways. Variability models can, for instance, be expressed as propositional formulas, context-free grammars (CFG) (Batory, 2005), or constraint satisfaction problems (CSP) (Benavides et al., 2005a,b). Accordingly, all configurations represent solutions to propositional formulas or CSPs, or valid words for CFGs respectively. That is, the generation of all configurations with respect to the variability model is equivalent to finding a solution or sentence for the aforementioned representations of a variability model. In the following, we review how variability models can be encoded as a CSP and describe in detail the configuration generation using CFGs.

3.2.1 Constraint Satisfaction Problem

A constraint satisfaction problem (CSP) in the context of variability modeling describes a set of options ranging over finite domains as well as a set of constraints which restrict the value range of a variable (Benavides et al., 2005a). For a binary option b, the respective domain $dom(b)$ simply is $\{0,1\}$. For a numeric option, the respective domain $dom(n)$ is a finite set of legal values with a minimum and a maximum value, say $\{v_{min}, v_1, v_2, \ldots, v_{max}\}$. A solution $s : O \rightarrow dom(o_1) \times dom(o_2) \times \ldots \times dom(o_{|O|})$ to a CSP is an assignment of options $o_i \in O, i \in \mathbb{N}$ to values of their respective domain, such that all constraints are satisfied simultaneously (Benavides et al., 2005a).

A solution to a CSP is found by systematically checking for different selections of values whether all constraints are satisfied. There exists a large number of ready-to-use SAT and CSP solvers, yet we are not covering CSP solution here since it is beyond the scope of the thesis. For further reading, (Benavides et al., 2007) present a tool with extensive analysis support for various different presentations of variability models.

To encode a variability model as a CSP, Benavides et al. (2005a) describe the following transformation rules:

- For a parent feature f and a child feature f', a mandatory relationship is expressed as $f \Leftrightarrow f'$, and an optional relationship is expressed as $f' \implies f$.
- For a parent feature f and child features f_i, where $i = 1, 2, \ldots n$, an or-group is expressed as $f \Leftrightarrow f_1 \vee f_2 \vee \ldots \vee f_n$, and an alternative-group is expressed as

$$\bigwedge_{i=0}^{n} f_i \Leftrightarrow (f \wedge \bigwedge_{j \in [0,n] \setminus i} \neg f_j)$$

.

To also consider numeric options, the domain of a numeric option n can be conceived as an alternative-group since only one value from the domain can be selected at a time. This is often called disretization of the domain. Hence, each value of the domain $dom(n)$

can be conceived as a binary option. If value $v \in dom(n)$ is selected, this states $n = v$, otherwise $n \neq v$.

3.2.2 Grammar Expansion

Besides trying to find a solution for satisfiability problems, the expression of variability models as context-free grammars (CFGs) enables the derivation of configurations directly from a CFG by expanding it. A first description of transformation rules, yet only for feature diagrams with binary options, was was proposed by Batory (2005). A hierarchical feature diagram can be recovered from a set of constraints using the algorithm of She et al. (2011) as explained in section 3.1.2. In the following, we describe how a feature diagram with both binary and numeric features can be transformed to a context-free grammar, and how configurations can be derived subsequently.

Def. 3.2.1 (Context-free Grammar)**.** *A context-free grammar is a tuple $G = (N, T, S, P)$, consisting of a set of non-terminal symbols N, a set of terminal symbols T, a start word $S \in (N \cup T)^*$, and a set of productions $P \subseteq N \times (N \cup T)^*$. The set L_G describes the language of the grammar G and comprises all valid words $w \in L_G$ which can be derived from the start word $S \in L_G$ by applying productions a finite number of times to it.*

Following the Definition 3.2.1, to derive all configurations for a given feature diagram, the idea is to first translate it to a context-free grammar. In order to do so, especially with respect to handling numeric options, we introduce an extended definition for a CFG, a configuration generation grammar.

Def. 3.2.2 (Configuration Generation Grammar)**.** *A configuration generation grammar is a context-free grammar $G = (N, T, S, P)$ whose elements are constructed from a feature diagram as follows.*

- *All features represent non-terminal symbols N, which can be divided into two disjoint sets, binary non-terminal symbols $F_{\mathcal{B}}$ and numeric non-terminal symbols $F_{\mathcal{N}}$. That is, $N = F_{\mathcal{B}} \cup F_{\mathcal{N}}$ and $F_{\mathcal{B}} \cap F_{\mathcal{N}} = \varnothing$.*
- *Similarly, the set of terminal symbols T is consists of two different sets, the binary terminal symbols $T_{\mathcal{B}}$ and the numeric terminal symbols $T_{\mathcal{N}}$, so that $T = T_{\mathcal{B}} \cup T_{\mathcal{N}}$ and $T_{\mathcal{B}} \cap T_{\mathcal{N}} = \varnothing$ with*

$$T_{\mathcal{B}} = \bigcup_{b \in F_{\mathcal{B}}} \{b_0, b_1\} \tag{3.1}$$

$$T_{\mathcal{N}} = \bigcup_{n \in F_{\mathcal{N}}} \bigcup_{v_i \in dom(n)} \{n_{v_i}\}. \tag{3.2}$$

- *All productions P are constructed from the hierarchy specified in the given feature diagram, the binary, and the numeric features. In our definition of a configuration grammar, each word w is expressed as a subset of (non-)terminal symbols, i.e., $w \subseteq (N \cup T)$. A word is a terminal word, if and only if it does not contain any non-terminal symbol. Accordingly, the set of productions is $P \subseteq N \times (N \cup T)$, and a production $p = (u, v) \in P$ is applied to a word w by removing non-terminal symbol*

u from word w and merging words v and w. Hence, the new word w′ is defined as $w' = (w \setminus u) \cup v$.

The productions $P = P_H \cup P_F$ *are constructed from the following disjoint two sets of productions:*

$$P_H = \{(p, \{c, c_1\}) | p, c \in N \wedge c \implies p\} \tag{3.3}$$

$$P_F = \bigcup_{f \in (F_{\mathcal{B}} \cup F_{\mathcal{N}})} \bigcup_{v \in dom(f)} \{(f, v)\} \tag{3.4}$$

- *Finally, the start word* $S \subseteq (N \cup T)$ *consists the non-terminal representing the top-level feature in the given feature diagram. The set of respective configurations is described by all words which can be generated by a finite number of applications of productions to the start word S.*

Based on Definition 3.2.2, we can specify an algorithm that computes the transitive closure of the grammar by repeatedly expanding each non-terminal for each (partial) word until a word containing non-terminal symbols is left. In addition to deriving all configurations from a grammar, the algorithm can also be used to derive partial configurations, such as binary-only configurations. To do so, the numeric features need to be removed from the set of non-terminal symbols. The only limitation of this algorithm is that, conceptually, it requires all numeric options to be mandatory features. This is due to the unspecified semantics of a numeric option being un- or deselected.

In the context of our methodology, configuration generation remains an intermediate step between the synthesis of a variability model and the selection of a meaningful sample set of configurations. The results obtained from applying both techniques, the encoding as a logical problem or the translation to a context-free grammar, to a variability model are equivalent. However, both techniques differ in terms of cost and tool support. While the former technique generally demands additional tool support, such as SAT or CSP solvers, their use is well established among research tools, such as *FeatureIDE* (Al-Hajjaji et al., 2016) or *SPLConqueror* (Siegmund et al., 2012). Moreover, research has shown that SAT solvers generally scale for large configurable software systems. In turn, the latter technique using context-free grammars can easily be implemented, yet the exhaustive expansion of a context-free grammar is infeasible and does not scale since all valid configurations are derived. Nonetheless, for handling smaller variability models, context-free grammar might be a makeshift solution.

3.3 Configuration Sampling

When assessing emergent properties for configurable software systems, it is infeasible to consider every possible variant. As previously stated in section 2.1, interactions between features can emerge, and can be the root cause for configuration-related performannce-interactions. Hence, effects on performance quality may be identified only under specific configurations. To not exhaustively assess all variants, a variety of strategies to select a sample set of configurations have been proposed. Every sampling strategy in the context of configurable software system is designed with respect to a *coverage criterion* (Apel et al.,

2013). While some coverage criteria take into account the coverage of feature interactions, such as t-wise sampling (Williams and Probert, 1996), others consider code coverage, such as statement coverage sampling (Tartler et al., 2014). Although configurations in our case can contain both binary and numeric options, we distinguish sampling strategies for both categories. In the following, we review a selection of popular sampling strategies for binary options as well as sampling strategies for numeric options, especially in the context of performance assessment.

Binary Features. Most sampling strategies in the context of configurable software systems target binary features. Popular sampling strategies for sampling configurations of binary features include, but are not limited to the following (Apel et al., 2013; Medeiros et al., 2016) strategies listed in Table 3.3.

Medeiros et al. (2016) have compared different sampling strategies, among other things with respect to resulting sample size and fault detection rate. *Most-enabled-disabled* results in the smallest sample size, whereas *t-wise* sampling, especially for a greater t yields the largest samples. Regarding the detection of faults, *statement-coverage* performed poorly, whereas *t-wise* sampled samples, especially with a greater t unveiled most faults. Note that sampling with respect to statement coverage is not applicable in the context of performance assessment since for performance measurements, the software system is generally conceived as a black box.

Numeric Features. Similar to selecting meaningful sample sets of binary options, for numeric options, sampling strategies are designed with respect to covering possible interactions. Subsumed under the term *design of experiments* various sampling strategies, or experimental plans have been proposed, each assigning values (from an option's domain) to independent variables (numeric options, in this case) (Antony, 2014). As the choice of an experimental plan (for both binary and numeric options) determines the number of measurements, and therefore the cost of assessment, not all designs might scale and be suitable for our assessments. Siegmund et al. (2015) have reviewed and evaluated a number of established experimental plans with respect to applicability in the context of configurable software systems. The authors exclude a number of designs due to an infeasible number of measurements, and advocate the use of four designs, including the Plackett-Burman Design and Random Designs. Assuming a discrete domain of values for each numeric option, the former design requires each combination of levels for each pair of numeric options to occur equally. The latter design is advocated not least because of an negligible number of constraints among numeric options (Siegmund et al., 2015). For further reading on more detailed descriptions of experimental designs, refer to Antony (2014).

In conclusion, finding a suitable sampling strategy remains a tasks with many aspects to consider. Depending on whether binary, numeric, or both types of configurations options are present, sampling strategies are selected, respectively. To derive mixed configurations, first, samples are selected from both binary and numeric configuration options. Second, the final sample of mixed configurations is computed as the cross-product of binary and numeric partial configurations. As stated by Siegmund et al. (2015), the treating binary and numeric options separately is justified since usually binary options enable or disable functionality while numeric options merely tune functionality. In the context of out methodology, a suitable sampling strategy might include combining different strategies,

Strategy Name	Description
Feature Coverage	Configurations are selected, so that each feature is selected in at least one configuration (Apel et al., 2013). An extension proposed by Sarkar et al. (2015) for projective sampling takes into account feature frequencies. The frequency of a feature is the frequency of the feature being selected or deselected in a sample set. As a coverage criterion, a specified minimum feature frequency is to be reached.
Most-enabled-disabled	Configurations are selected, so that a maximal and minimal number of features is enabled (Medeiros et al., 2016).
One-enabled	Configurations are selected, so that each feature is enabled at a time (Siegmund et al., 2012). Similarly, with a *one-disabled* strategy, configurations are chosen, so that each feature is deselected at a time.
Random Sampling	Configurations are selected randomly, i.e., for a configuration, for each optional feature a random value out of 0 or 1 is assigned. Guo et al. (2013) have studied learning performance of a configurable software system from a random sample with acceptable accuracy.
Statement-coverage	Configurations are selected, so that each variable block of code (for compile-time variability) is at least included in one variant (Tartler et al., 2014). This either applies to variable code sections via preprocessor annotations, or to entire files and compilation units.
T-wise sampling	Configurations are selected, so that all t-tuples of all (binary) features are included in at least one configuration (Williams and Probert, 1996). That is, the upper bound for the sample size is $\binom{\lvert F\rvert}{t}$ for features F and $t \in \mathbb{N}$. Siegmund et al. (2012) extend this approach by composing higher-order feature tuples ($t > 2$) from already known pair-wise interactions. The rationale behind this heuristic is that, if pairs of features interact, also tuples including those pairs are likely to interact.

Tab. 3.3. Selection of sampling strategies for binary features.

either due to different types of configuration options, or due to multiple coverage criteria to meet. As a guideline for selecting a sampling strategy, especially in the context of performance assessment, no clear recommendation can be given. However, from samples selected via random sampling (Sarkar et al., 2015) and pair-wise sampling (Siegmund et al., 2015) have shown acceptable results in terms of accuracy.

4 Methodology: Version Assessment

In the last chapter, we have covered means to understand variability, synthesize variability models for a given software system, and to select sample sets of configurations. To enable the assessment of performance evolution for configurable software systems, the next step in our methodology takes into account the dimension of diachrony. As software evolves, multiple versions, or called revisions, of a software system exist. In this chapter, we address the question of how we can assess performance for multiple revisions. Moreover, we ask whether we can describe a configurable software systems' performance evolution without exhaustively assessing all versions by selecting only a sample set of versions. As illustrated in the methodological road-map in Figure 4.1, we summarize these two questions with the task of revision sampling.

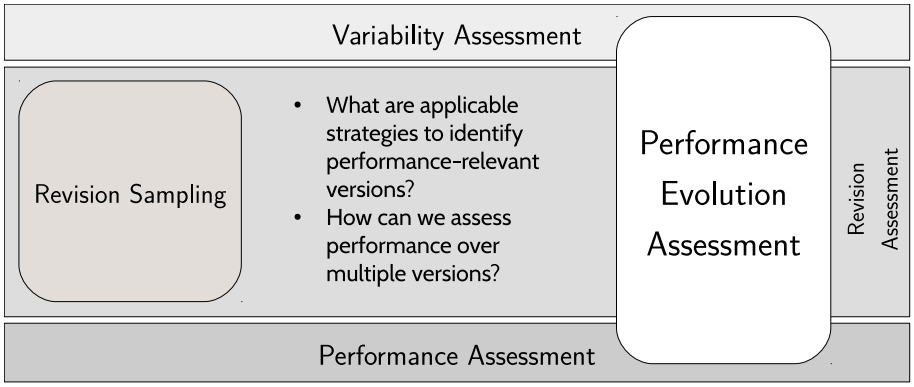


Fig. 4.1. Methodological road-map: questions to address with revision assessment.

The chapter is organized as follows. In section 4.1 we present the methodological requirements for a designing and selecting a revision sampling strategy. In section 4.2 we propose four approaches to revision sampling based on observations of configurable software systems. In section 4.3 we evaluate the different approaches against exhaustive measurements of a selection of configurable software systems. Finally, in section 4.4 we conclude the chapter and discuss the approaches' applicability in the context of our methodology.

4.1 Towards Revision Sampling

Research so far has addressed the assessment of a software system's revision history under the umbrella of repository mining, for instance, to localize bugs (Moin and Khansari, 2010) or performance regression (Heger et al., 2013). Nonetheless, so far there exists little to no research addressing the question what the choice of versions might reveal about performance evolution. The task of selecting resources and a sample set of versions to analyze can be conceived as a sampling strategy, where the objective is to cover interesting

entities (performance changes, in our case) while trying to limit the sample size to keep the required effort reasonable. Before we present different approaches to select a sample set of revisions, we need to define general cornerstones for evaluating a sample set of revisions as well as respective revision sampling strategies with respect to performance change history.

Revision Sample Set. The first question is, what criteria we take as a basis for rating a sample set of revisions as *meaningful*. First, our intention is to obtain a representative description of a software system's performance change history while only assessing a fraction of revisions. That is, assessing a representative sample of revisions should yield a performance change history similar to the assessment of all revisions. Since we are interested in revisions for which performance measurements change, these revisions should be contained in a representative sample. Second, especially in the context of variability, a performance change might only affect a subset of the assessed configurations. A representative sample set, therefore, should describe a history of significant performance changes with respect to all variants assessed. We consider a performance change to be significant, if it affects a significant portion of the sample of variants (*effect range*) and if the relative change in performance measurements is significantly large (*effect magnitude*).

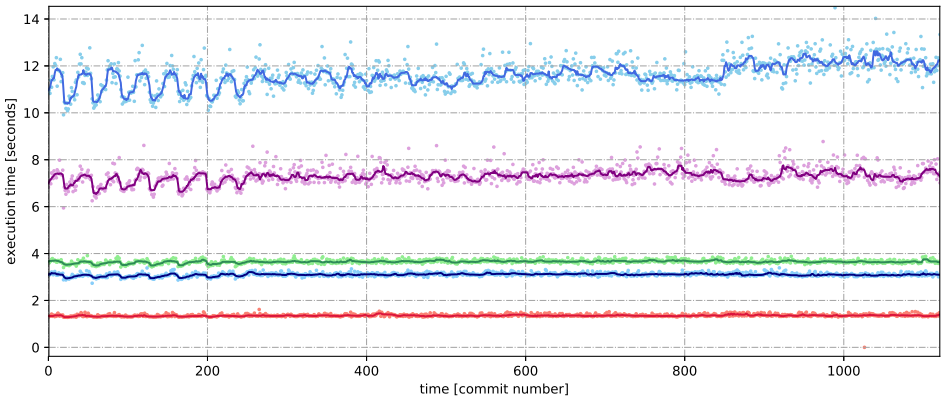


Fig. 4.2. Performance History for XZ

To illustrate the two facets of performance changes, in Figure 4.2 we see a history of performance measurements (execution time in this case) for a small-scale configurable software system, file compression tool called *GNU XZ Utils*. The graphic depicts execution time measures for executing a standard compression benchmark for 1,135 different versions and covers a version history of about nine years.

In this excerpt, we only show the execution time measures of five different variants, i.e., each version was assessed with five different configurations. Each performance measurement is depicted by a single marker. In addition, we provide a plot of a moving median, to identify trends. We see that each variant has a certain performance level, and overall, the performance measurements remain stable. While the blue and purple variant are generally more volatile, for all variants, we see performance measurements oscillating during the first 250 versions. With regard to the two facets of significance mentioned earlier, not all variants are affected similarly by this effect to the same degree.

While the former significance criterion can unambiguously defined by a threshold number of variants, for the latter one one needs to define how to summarize relative performance change among all variants. For instance, a performance change may have a significant magnitude, if the average deviation of performance measurements for all variants is greater than a specified threshold value.

Revision Sampling Strategies. The second question addresses the rationale behind a revision sampling strategy. To obtain representative sample sets, sampling strategies are intended to utilize knowledge about the total volume to select sample sets from. For instance, pair-wise sampling aims to cover most feature interactions. Similarly, we demand for a meaningful revision sampling strategy to exhibit a certain rationale or coverage criterion. If we conceive a sampling strategy as a binary classificator that, in our case, decides whether in a revision a performance change is likely, or performance measurements might have changed compared to prior commits, we want this classifier to be sensitive, i.e., to have a preferably high true positive rate. That is, a sampling strategy is meaningful if we learn which revision features most likely indicate performance changes.

In conclusion, when designing a revision sampling strategy, we ask for a plausible rationale or coverage criterion with respect to performance changes. A resulting sample set of revisions, in addition, is representative, if the contained revisions sketch performance changes. For the context of this methodology, we remain with a clear definition of what performance changes are significant. Based on these assumptions, in the next section we propose a selection of four revision sampling approaches based on different observations.

4.2 Revision Sampling Strategies

As there are no established approaches to select sample sets of versions for configurable software systems, especially with respect to performance assessment, in the following five subsections, we propose five different strategies to address this problem. Our proposals utilize different sources of information regrading the software system studied, and are inspired by approaches that have proven to be applicable in different contexts. An overview and classification of the five proposals is presented in Figure 4.3. Our approaches can be grouped into two categories. The first category incorporates meta-data about a commit, including its lifetime (how long it has been the latest commit), and the number of lines of code modified by it. For the first category, sampling strategies intend to achieve high coverage of the overall version lifetime, or modifications, respectively. The proposals listed in the second category may as well use take into account meta-data, yet for a different purpose. The classification-based proposals use meta-data along with performance measurements to learn and predict the likelihood of a commit introducing performance changes. The remaining approach, in the overview referred to as performance history approximation, adapts the bisection approach by Heger et al. mentioned earlier. The approach continuously expands a sample set until no performance-changing commits can be identified.

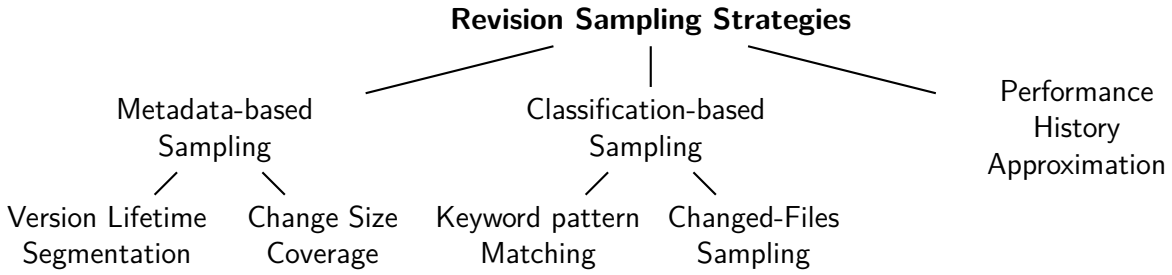


Fig. 4.3. Overview of our proposed revision sampling strategies.

4.2.1 Keyword Pattern Matching

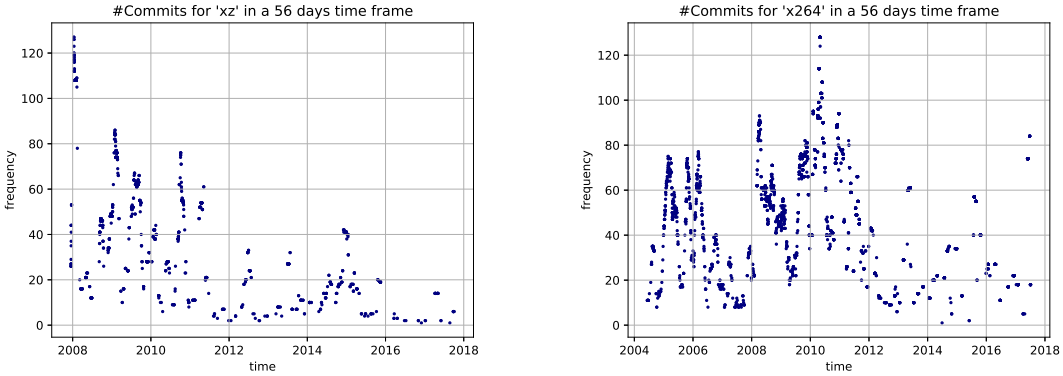
The first version sampling strategy we present is driven by the conception that a commit message usually summarizes the changes of a commit in terms of what has been implemented, modified, removed, or what problems have been fixed. Commit messages can include keywords or phrases that indicate a performance context, such as "fixed performance bug ...", or exhibit information about the version of the software system, such as "bumped version number to ...". Based on this information, we propose to use pattern matching to check whether a commit message contains a keyword that might indicate a performance context, or a new version, respectively. The sampling algorithm works as follows. Given a set of keywords, such as "performance, bug, fix, slower, faster, ...", we first derive the word stems for each keyword. Second, for each commit message, we split the message into separate words and derive their corresponding word stems. Third, we match all sets of resulting word stems (one set per commit message) against the set of keyword sets and retain those commit messages, for which sufficiently word stems are contained. As these commit messages contain our previously defined keywords, we select the corresponding commits as our version sample set.

This approach is simplistic and its accuracy clearly depends on the quality of the initial selection of the keyword set. Moreover, more sophisticated ways to compute similarity between texts, such as the tf-idf-measure and various similarity metrics (Huang, 2008). However, we only propose this strategy to evaluate the overall applicability of approaches driven by text similarity to the problem of version sampling.

4.2.2 Version Lifetime Segmentation

The second approach to select sample versions from the history of versions is based on assumptions and observations obtained via repository mining. The following approach is driven by the assumption that performance changes are more likely to occur when the software system is revised frequently in a short period of time. Not only is this simply due to a higher number of revisions. We can also assume that if a software system has not been revised for a long period of time, changes in terms of performance-relevant fixes were not necessary, or have been deferred. Although postponing performance-relevant fixes has become sort of a virtue (Molyneaux, 2014), for the latter case the can exist other reasons, including organizational constraints or performance issues being undetected at that time. That is, we assume that those versions that have been the latest version for a long time due to the absence of changes as well as the necessity thereof can sketch a software systems performance history. We do not assume that long-lasting versions introduce performance

changes, but they enable the segmentation of a software systems version history in a way that it represents a large portion of the software systems lifetime.



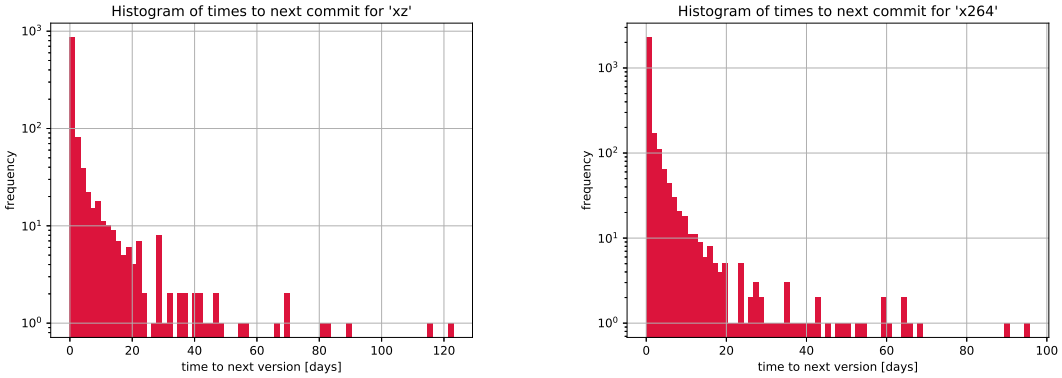
(a) Activity graph for `GNU XZ`, generated from 1,135 versions between December 8, 2007, and August 14, 2017.

(b) Activity graph for `x264`, generated from 2,851 versions between June 3, 2004, and June 26, 2017.

Fig. 4.4. Commit activity for two sample systems, the compression utility `GNU XZ` and the video encoder `x264`. For each version, the activity is measured as the number of commits that were pushed within a certain timeframe of eight weeks.

Making the connection with our methodological context and the aim to design a version sampling strategy, we intend to achieve a high "lifetime coverage" with a small number of versions. For this reason, we have evaluated the "lifetime" of versions of different software systems. In the following, lifetime of a version or commit refers to the period of time between a commit and its successor. We have investigated the distribution of version lifetime for two open-source software systems, a free file compression tool, *GNU XZ*, and a free video encoder, *x264*. – This selection is by far not representative, yet the observations obtained from systems document our assumptions. Since we will refer to those two and other systems for the evaluation, we answer how and why these systems were selected in the evaluation in chapter 5. – The first observation regarding the lifetime of single versions is illustrated in Figure 4.4 for the two software systems, respectively. The figure, for each version, shows the activity during development of both systems. For each commit, we have counted the number of commits preceding and succeeding it within a four week time frame, respectively. One can see that for both software systems we can identify spikes with a high commit frequency as well as plunges with little to no commit activity. Moreover, if we look at the histogram of all commits lifetime for both systems respectively as illustrated in Figure 4.5, we see that there actually are many commits with a short lifetime (activity spikes) as well as only very few commits with a long lifetime (plunges).

Based on the aforementioned assumptions as well as the distribution of version lifetimes, when translating this in the context of a version sampling strategy, we can achieve high "lifetime coverage" by selecting very few versions from a list of versions sorted by lifetime in descending order. This sampling strategy picks the longest-lasting commits until a desired coverage threshold, or version threshold number is reached. This sample selection of commits is a segmentation or clustering of the overall version history. We assume that each segment represents a (sort of) steady state of the software systems performance



(a) Distribution of time to next commits for `GNU XZ`

(b) Distribution of time to next commits for `x264`

Fig. 4.5. Distribution of time to next commits for two configurable software systems, measured as the distance between a commit and its successor.

history.

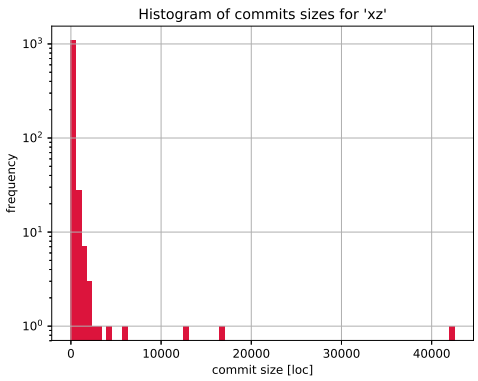
4.2.3 Change Size Coverage

The third approach we propose adapts the idea of the previously mentioned version lifetime segmentation. The following sampling strategy design is driven by the assumption that a version or commit is more likely to introduce performance changes to a software system if it modifies a large portion of code. We assume that the effect of modifying a single line of code is not as significant as modifying multiple lines of code. Of course, modifications can accumulate, or trigger already existing interactions, yet from a black-box perspective, commits affecting more lines of code are more likely to introduce performance changes or to trigger interactions. That is, for designing a version sampling strategy, we aim to cover most of all changes made to the software system with a few number of versions. Similar to the assessment of version lifetime in Figures 4.4 and 4.5, we have investigated the distribution of commit sizes in terms of lines of code for the two software systems *GNU XZ* and *x264*. As illustrated in Figure 4.6, we see that, by far, most commits modify less than 2,000 lines of code, whereas very few commits modify or add larger code sections.

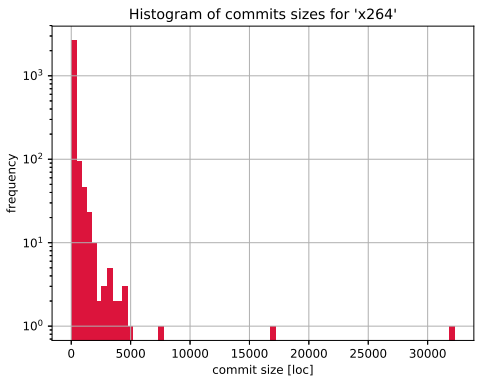
Based on these observations and given the assumption that larger commits are more likely to introduce performance changes, we propose to obtain a sample of versions by selecting versions from a list of versions sorted by commit size in a descending order. Similarly to version lifetime segmentation, one can specify a threshold of sample set size or commit size coverage to achieve. We assume that a sample set of versions obtained using this approach is likely to cover significant performance changes since a larger portion of the overall change history is covered.

4.2.4 Performance History Approximation

The next sampling strategy that we propose is an adaption of the revision sampling approach used by Heger et al. (2013). For a software system's version history along with



(a) Distribution of changed lines per commit for `GNU XZ`



(b) Distribution of changed lines per commit for `x264`

Fig. 4.6. Distribution of commit sizes in lines of code for two configurable software systems, `GNU XZ` and `x264`.

test cases and corresponding performance measurements, the authors aim to identify those commits which may have introduced performance regression. The authors have used a binary-search-like approach to iteratively bisect the version history to find commits for which performance measurements deviate significantly from previously measured ones. Once a relevant commit is identified, it can be subject of further root-cause analysis.

We adapt this approach to extract performance-relevant commits given an initial sample of versions along with performance measurements. A performance-relevant commit in this context is a commit for which performance measurements significantly deviate from measurements of previous commits. The sampling strategy is applied as follows. Given an initial sample of n versions and corresponding performance measurements, the version history is segmented into $n-1$ segments. Each segment is clearly specified by two commits. For each segment s_i, the algorithm now computed the difference in performance measures δ_i for the start and the end commit. For the largest differences, the segment is bisected. For the resulting two segments δ_{i_1} and δ_{i_2}, the performance measurement differences are calculated. If the absolute difference between δ_{i_1} and δ_{i_2} is greater than zero, one of the two children segments is "steeper", i.e. has a greater performance measurement difference than the parent segment as exemplified in Figure 4.7. One can specify a minimum threshold difference to retain those resulting segments. This procedure is repeated until no further segments can be bisected without violating the

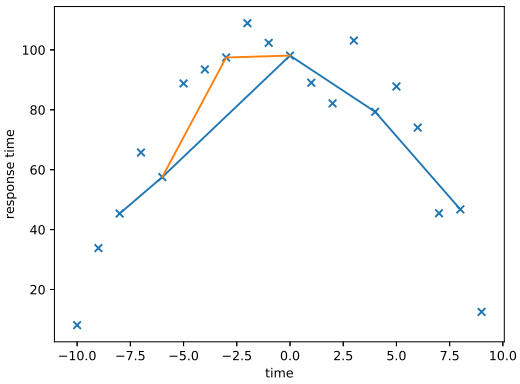


Fig. 4.7. Given a initial sample of five versions and four segments (blue line), the steepest segment is bisected and replaced by two segments (orange). The first of the orange segments is steeper than the segment that was bisected.

minimum performance difference threshold. That is, the algorithm approximates an interpolation of the overall performance history while focusing on sketching the steepest changes.

4.2.5 Changed-Files Sampling

The last version sampling strategy that we are going to present is a binary classifier that predicts whether a commit is likely to introduce performance changes. The idea behind this classifier is that performance changes might depend on changes in specific code sections or combinations thereof. For each commit we can retrieve which code sections, or files have been touched. If there exists a relation between a commit's file change set and performance changes, one could learn it and predict performance change likelihood for arbitrary commits.

We propose a sampling strategy that based on a random initial sample learns a possible relation between a commit's set of changed files and performance changes. For each commit in the initial learning sample, the performance difference to the previous commit is calculated. Since we are interested in any change in performance, not only performance degradation, we consider the absolute performance difference as the performance change introduced by that commit. Consequently, using classification and regression trees (CARTs), we approximate a function that maps a commit's set of changed files to it's absolute performance change. If the classificator is accurate enough, it can be used to select the commits that are most likely to introduce performance changes.

4.3 Strategy Evaluation

- Quality criteria / performance history similarity

4.4 Methodological Remarks

5 Methodology: Performance Assessment

5.1 Performance Benchmarks

How performance benchmarks should be chosen...

5.2 Profiling

Which tools exist to profile programs, such as `GNU time`, ...

5.3 Statistical Considerations

In this section, we now discuss the appropriate statistical means to summarize, compare and interpret measurement results. For the remainder of this section, we will refer to the following two scenarios. First, to obtain robust results, the assessment of a single variant needs to be repeated multiple times. Consequently, to report a single result per metric, the measurements for a single variant need to be summarized. Second, the assessment of performance for a variant may comprise several use cases, for instance file compression and decompression for a compression software. Therefore, performance measures aggregated from different benchmarks need to be summarized accurately.

5.3.1 Measures of Central Tendency

For each test run of a software system or variant, we obtain a single-valued measurement per performance metric. Since we repeat each test run n times per variant, we obtain a data record X with n measurements $X = X_1, X_2, \ldots, X_{n-1}, X_n$. While the arithmetic mean is commonly considered the right way to summarize data records and report a representative average value, we need to be more cautious with how to summarize data records (Fleming and Wallace, 1986; Smith, 1988). From a statistical perspective, the intention of summarizing a data record is to find a measure of central tendency what is representative for the data record. While the arithmetic mean is an appropriate method for many cases, there exist other means to summarize data records. Moreover, there exist a number of criteria for when to use which means to summarize a data record.

The first question when summarizing a data record is to ask what the data actually describe and what we intend to express with our summary. For a data record X, we can define a relationship we would like to conserve while replacing each single X_i with an average value $\bar{x}$. Based on this relationship, we can derive the appropriate method to summarize our record. For instance, our data record X describes the time elapsed

for a test case and we want the keep the following relation, saying that the sum of all measurements $\sum_{i=1}^{n} X_i$ is equal to the total time elapsed T, defined as

$$T = \sum_{i=1}^{n} X_i = \sum_{i=1}^{n} \bar{x}.$$

Based on the term above, we can derive the definition of the method appropriate to summarize our data record with respect to the conserved relation what is the *arithmetic mean*, defined as

$$\bar{x} = \frac{1}{n} \sum_{i=1}^{n} X_i. \tag{5.1}$$

Consider another example, similar to the one above, where the test case is a load test with a predefined number of users and the measurements $X = X_1, X_2, \ldots, X_{n-1}, X_n$ are measured as hits per second. Again, we have different measurements we want to summarize with respect to a relation to conserve. Each user drops the same number of requests T, whereby the hit rate X_i and the respective elapsed time $t_i = \frac{T}{X_i}$ vary. We now conserve the relationship that the total number of requests for the data record is the sum of all hit rates X_i times the time elapsed t_i. Therefore, we want to substitute each hit rate X_i with an average value $\hat{x}$ so that the aforementioned relationship is conserved:

$$n \cdot T - \sum_{n}^{i=1} X_i t_i = 0 \Leftrightarrow n \cdot T - \hat{v} \sum_{n}^{i=1} t_i = 0 \Leftrightarrow n = \hat{x} \sum_{n}^{i=1} \frac{1}{X_i}$$

Similar to Eq. 5.1 we can derive the definition for the summarization method to use from the equation above what is the *harmonic mean*, defined as

$$\hat{x} = n \cdot \left(\sum_{i=1}^{n} \frac{1}{X_i} \right)^{-1} = \frac{n}{\frac{1}{X_1} + \frac{1}{X_2} + \ldots + \frac{1}{X_{n-1}} + \frac{1}{X_n}}. \tag{5.2}$$

We see that the summarization methods presented in Eq. 5.1 and 5.2 are useful for different types of data records, and should be used accordingly. The arithmetic mean is suitable for records, where the total sum of single measurements has a meaning, whereas the harmonic mean is suitable for measured rates or frequencies (Smith, 1988).

While the aforementioned measures of central tendency should be appropriate for most cases, they are not always the best choice though since the arithmetic and harmonic mean are heavily influenced by extreme observations (Shanmugam and Chattamvelli, 2015). For instance, for the data record $X = 1, 2, 3, 30$, three of four values are smaller than the arithmetic mean $\bar{x} = 9$. One option is to explicitly exclude outlier values from the data record. The so-called *trimmed mean* is obtained by truncating a upper and/or lower percentage t of the data record and, consequently, computing the (arithmetic or harmonic) mean for the remaining data record (Shanmugam and Chattamvelli, 2015).

While this method is suitable to omit the effects of outliers, one still needs to specify which upper and/or lower percentage t needs to be truncated. Moreover, the use a (trimmed) mean requires the data records' frequencies to be distributed symmetrically around its mean. A probability distribution is skewed (and therefore asymmetric) if,

graphically speaking, its histogram is not symmetric around its measure of central tendency. A simple method to measure the skewness of a probability distribution is *Bowley's measure* (Shanmugam and Chattamvelli, 2015), defined as

$$B_S = \frac{(Q_3 - M) - (M - Q_1)}{Q_3 - Q_1} = \frac{(Q_3 + Q_1 - 2M)}{Q_3 - Q_1}, \tag{5.3}$$

where Q_1 and Q_3 denote the first and third quartile, and M denotes the median of the probability distribution. The quartiles Q_i with $i \in \{1,2,3\}$ are defined as the values of a data record X, so that $\frac{i}{4}$ of the values of X are smaller than Q_i. The *median* is defined as Q_2, i.e., a value $M \in X$ so that half of the values in X are smaller than M.

The median itself is a more robust measure of central tendency than the aforementioned ones since it is less influenced by outliers and can be used for both skewed and symmetric data records (Shanmugam and Chattamvelli, 2015). For a given ascendingly ordered data record $X = X_1, X_2, \ldots, X_{n-1}, X_n$, we can compute the median as follows:

$$\text{Median}(X) = \begin{cases} X_{\frac{n+1}{2}} & \text{if } n \text{ is odd} \\ \frac{1}{2}\left(X_{\frac{n}{2}} + X_{\frac{n}{2}+1}\right) & \text{if } n \text{ is even} \end{cases} \text{ with } X_i \leq X_j \text{ and } i < j \leq n \tag{5.4}$$

5.3.2 Measures of Dispersion

Last, we take a look at different measures of spread or dispersion. Most commonly used are the *variance* σ^2 and the *standard deviation* $\sigma = \sqrt{\sigma^2}$ defined along the mean μ of a probability distribution as

$$\sigma^2 = \frac{\sum_{i=1}^{n}(X_i - \mu)^2}{n} \tag{5.5}$$

Similar to the (arithmetic or harmonic) mean, the variance and the standard deviation are heavily influenced by extreme observations (Shanmugam and Chattamvelli, 2015) and not the best choice in all cases. Instead, two more robust measures are the *median absolute deviation* (MAD) and the *inter-quartile range* (IQR). The MAD is defined as the median of the absolute deviations from the probability distributions' median (Molyneaux, 2014), or, defined as follows:

$$\text{MAD}(X) = \text{Median}\Big(|X - \text{Median}(X)|\Big) \tag{5.6}$$

The IQR, however, defines the range between the first and the third quartile, Q_1 and Q_3 (Shanmugam and Chattamvelli, 2015). This range is larger for a widespread data record and smaller for a data range with a narrow spread, but is not influenced by extreme observations as those outliers do not lie within the range $[Q_1, Q_3]$. The IQR is defined as

$$\text{IQR}(X) = Q_3 - Q_1. \tag{5.7}$$

5.3.3 When to use which measure?

In this section we discussed the arithmetic and harmonic mean as well as the median as a measure of central tendency, the symmetric property that is required to use the arithmetic or harmonic mean, and different measures of spread for a given data record. At the beginning, we have raised the question of how to summarize data records (a) for an experiment repeated multiple times, and (b) obtained from different benchmarks. While for case (b) the answer is to use the arithmetic or harmonic mean (depending on the quality of the measurements), for (a) the answer is a little more elaborate.

The arithmetic (or harmonic) mean can be used whenever the quality of the measurement is appropriate and the data record is symmetric. According to Shanmugam and Chattamvelli (2015), the arithmetic mean is preferable "when the numbers combine additively to produce a resultant value", such as time periods or memory sizes, whereas the harmonic mean is preferable "when reciprocals of several non-zero numbers combine additively to produce a resultant value", such as rates or frequencies (Smith, 1988). The median is a less precise estimator than the both means, yet more robust with regard to extreme observations. In addition, the MAD or IQR provide a more robust means of spread than the standard deviation.

5.3.4 Systematic Error

How different machines can be used to minimize systematic error

5.4 Summarization Strategies

- How to summarize performance for a single version?
- Minimal/Maximal configuration, best/worst performance measurement, ...

6 Evaluation

7 Conclusion

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