Measuring Non-functional Properties in Software Product Lines for Product Derivation

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Abstract

Software product lines (SPLs) enable stakeholders to derive different software products for a domain while providing a high degree of reuse of their code units. Software products are derived in a configuration process by combining different code units. This configuration process becomes complex if SPLs contain hundreds of features. In many cases, a stakeholder is not only interested in functional but also in resulting non-functional properties of a desired product. Because SPLs can be used in different application scenarios alternative implementations of already existing functionality are developed to meet special non-functional requirements, like restricted binary size and performance guarantees. To enable these complex configurations we discuss and present techniques to measure non-functional properties of software modules and use these values to compute SPL configurations optimized to the users needs.

1 Introduction

Software product lines (SPLs) are developed to create a large amount of related products by reusing a set of software artifacts called core assets or simply *code units* [10, 19]. These code units, once developed and tested, can be composed into different products with varying functionality. This decreases development effort and time-to-market while providing a high degree of reuse [16].

The functionality of an SPL is represented as features [18, 11]. *Product derivation* is the process of generating a tailor-made product of an SPL. It consists of (1) selecting features (functionality) according to stakeholder requirements, (2) checking the consistency of the selection, and (3) composing code units to generate the product. Even in small SPLs a manual selection is often a complex task [14]. If the user has additional non-functional requirements, e.g., binary size $<$ 100kByte because the device he uses has this memory size, the derivation process becomes even more complex and difficult. SPLs of industrial size can have thousands of features [32, 20] which makes a manual product derivation usually impossible. Current research addresses this problem by providing visualization techniques and special algorithms to reduce the complexity of the configuration process [33, 7, 35]. While these approaches are successful for functional requirements they do not address non-functional requirements.

Environments like embedded systems or large scale computing systems have such non-functional requirements like restricted memory [4], power consumption [3, 27], and performance requirements [22, 2]. Current research for *Green IT* (power awareness) strengthens the need for tailor-made, alternative implementations to reduce power costs [9, 15]. For example, a sorting algorithm in an SPL can be implemented to minimize the binary size, maximize the performance, or reduce the power consumptions. However, there is no overall best implementation. A stakeholder is now able to chose which implementation of the sorting algorithm fits best to a particular application scenario. Each implementation has a different impact on the non-functional properties of a product which cannot be foreseen. Already the product derivation with a functional selection is a complex task, but how can we provide a production derivation with additional non-functional requirements? The selection of functionality that must be part of a product is not enough any more and the best implementation for an application scenario has to be chosen. Such non-functional requirements can be expressed by defining an objective function to maximize or minimize a set of non-functional properties.

In this paper, we present an approach to optimize products toward non-functional properties. To enable this process we address two important steps. First, we explain how to measure non-functional properties and how they can be obtained for a feature selection. Second, we present an algorithm to optimize a product configuration according to user-defined non-functional requirements. We evaluate our approach in a case study using the non-functional properties *Maintainability*, *Binary Size*, and *Performance*.

2 Software Product Lines

SPLs are used to derive different related products from a common code base that belong to one domain [10, 19]. Different programs differ in features, e.g., one database management system (DBMS) product has feature *Recovery*, another has not. These differences are so called *variation points*. The features of an SPL and relationships between the features are describe in a feature model with additional information like attributes or annotations [18, 11]. A feature model defines if a feature is optional or mandatory. A typical visualization of a feature model is a feature diagram that is a hierarchical representation of all features of an SPL where the top most feature represents the domain concept (cf. Figure 1). To derive a product a stakeholder selects the features from a feature diagram that fulfill her functional requirements. The process of selecting features and verifying the correctness of the selection against constraints makes the derivation process.

To incorporate non-functional properties, in previous work, we [30] and others [7] extended the common feature model concept. The basis of our product derivation process is our *product line model (PLM)* [30]. Specifically, we distinguish between domain variation points (features) and implementation variation points (code units). This gives us the possibility to express variability of the implementation which bridges the gap between functional variation (in terms of features) and non-functional variation (in terms of code units). For example, a domain variation point in a DBMS SPL is feature *Transaction*. This feature introduces new functionality and allows new product variants. An implementation variation point in this DBMS is represented in multiple implementations for the feature *Search Index*, e.g., *B-Tree*, *Hash*, and *Queue*. Thus, the user can choose the implementation of a feature that fits best to her non-functional requirements.

Figure 1 depicts a small example of a feature diagram generated from a PLM. The model represents a DBMS SPL. Feature *Sort* is implemented with two alternative code units, a power saving optimized *JouleSort* [34] and a performance optimized *MergeSort*. When choosing the feature *Data Sorting* the stakeholder has to decide which implementation fits best to the non-functional requirements of the product. In this example, the *JouleSort* algorithm could be selected to minimize the power consumption. In contrast, the *MergeSort* algorithm has a smaller binary size. Considering the binary size of other variation points, it is difficult to decide if a feature selection violates a binary size constraint. For large SPLs this can lead to a time-consuming ”trial and error” process.

3 Measuring Non-functional Properties

Before optimizing configurations of SPL products, we need to measure the non-functional properties. We measured non-functional properties for a refactored version of Berkeley DB SPL[1]. Using *feature-oriented programming* [26, 5] the refactoring results in 36 features and 400.000 possibile products. First, we wanted to measure all products but very soon we recognized that this approach does not scale. A simple performance measurement for one product takes about 9 minutes including compiling this product and executing the benchmark. This means a complete measurement including all products would take about 2500 days. Hence, we cannot simply measure each variant of that SPL.

Instead, we aim at measuring the non-functional properties of features. This is more complex as expected because not every non-functional property can be mapped intuitively to a single feature. For example, some properties emerge only in running programs and depend on the interaction of multiple features. For those properties, each SPL instance has to be measured to derive the optimal product. In the following, we discuss techniques and a classification for the measurement of non-functional properties.

3.1 Classes of Non-functional Properties

Our analysis has shown that non-functional properties can be categorized into three different classes, *Direct Assigned Properties*, *Inferred Properties*, and *Runtime Properties*. This categorization helps us to select the appropriate measurement technique for a non-functional property.

The first class, **Direct Assigned Properties**, contains properties that are fully or partly represented as features because the direct selection by a stakeholder is reasonable. For example, reliability does not emerge during the development or product derivation. It can be directly ascribe to features and allows its configuration according to reliability requirements, e.g., *Recovery* in Figure 1. During measurement, we do not have to care about these kinds of properties because they are assigned manually and selected manually.

Non-functional properties of the category **Inferred Properties** are either measured in isolation for each feature or the values for features are inferred from one or a few products. This means, we annotate values for non-functional properties to features and code units. This allows us to compute emerging non-functional properties for arbitrary product configurations in advance. To do this, we have to aggregate the values of the properties. There are different possibilities to aggregate the values. For example, if we can measure the binary size per feature we can simply compute the size of the product by summing the values of

[1] HTTP://WWW.ORACLE.COM/DATABASE/BERKELEY-DB/DB

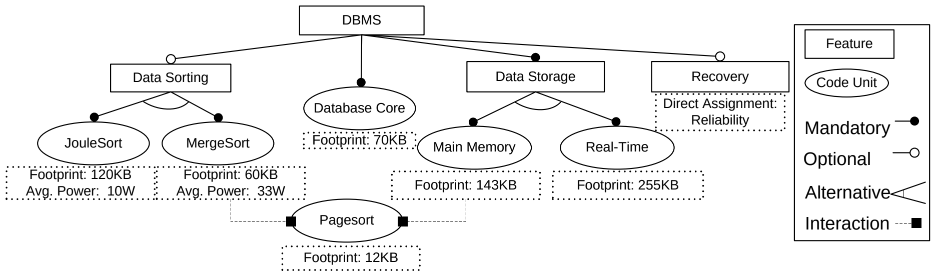


Figure 1. Simple Product Line Diagram.

each configured feature (see Figure 1). The method used for aggregation depends on the application scenario and the non-functional property and has to be defined by a stakeholder.

Finally, the **Runtime Properties** class is the most complex class for measurements. These non-functional properties emerge in a compiled and running product. Prominent examples are performance, power consumption, and object size in main memory. Feature interactions have a major influence on these properties that an inference from code units is not possible or has an unacceptable fault rate. Thus, we have to measure concrete products which leads to a combinatorial problem reasoned by the large number of possible products.

We present our approach for measuring three important non-functional properties, namely *Maintainability*, *Binary Size*, and *Performance*. We chose these properties to have representatives for the categories *Inferred Properties* and *Runtime Properties* that require measurements. In addition, these are common properties that are used in practice.

3.2 Measuring Maintainability.

Maintainability describes how much effort it is to correct, extend, or simply maintain the a software system or component [1]. Maintainability is especially important during software development and evolution. To ensure maintainability application engineers structure code units into components or packages. Source code guidelines often hints how to write maintainable code [24]. It is a difficult task to rate or to quantify the code quality. Several metrics were proposed to rate and compare source code fragments. Because of the wide acceptance in research, we choose the metric cyclomatic complexity [23] for our measurement, but other metrics can be used as well. The resulting values of such metrics can be aggregated. We choose the maximum for cyclomatic complexity to express the difficulty of maintaining the source code. So that the maintainability of the worst module represents the maintainability of the product.

Source code measurements in SPLs can be applied to

Feature	Cyclomatic Complexity
Cryptography	19
Remove	20
Hash	70
Maximum	70

Table 1. Measurement of Cyclomatic Complexity of Berkeley DB.

code units for each feature separately. This way the maintainability is categorized as an *Inferred Property*. The maximum complexity of the whole feature is the maximum complexity of each method that belongs to this feature. We show in Table 1 a measurement of the Berkeley DB SPL. A number higher than 25 for the cyclomatic complexity represents poor written code that might be difficult to understand. That means feature *Hash* appears to be very difficult to maintain. Depending on the configuration the maintainability for the product can significantly change. If the feature *Hash* is chosen the complexity increases to 70 which means that the code of the resulting product will be difficult to understand. For the computation of the resulting complexity we have to include all scattered code values that belong to a configuration. To achieve the correct value for an SPL product we store the cyclomatic complexity for each class fragment that belongs to a certain code unit, separately. We use the existing tool *Source Monitor*[2] to measure the cyclomatic complexity and store the obtained values within the PLM.

3.3 Measuring Binary Size.

At first sight, it seems that the binary size has to be measured for each compiled product variant. However, a mapping from the binary size of a product to features is possible, e.g., by extracting the delta size for different products. For SPLs implemented by separately compilable code units, e.g., components or Hyper/J [25], a measurement is trivial. But using preprocessor statements or feature-oriented

[2] http://www.campwoodsw.com/sourcemonitor.html

programming the measurement becomes difficult because the source code is scattered over small non-compilable modules. Actually, we developed a technique for feature-oriented programming (used in our case studies) to extract the binary size by including all features into one binary. Our tool extracts the binary size for each method from information generated by the Microsoft C++ compiler. The size of a feature is the sum of all methods that belongs to this feature. Therefore, the binary size can be classified as an *Inferred Property*. We had to disable function inlining to assign the binary size of a method to the correct feature. The impact of function inlining was negligible in our case studies, shown in Section 5.

3.4 Measuring Performance.

The last non-functional property, we want to address in this paper, is performance. This non-functional property only emerges in a running product, thus, cannot be calculated in advance (*Runtime Property*). This leads to the combinatorial problem of testing and measuring all possible products of an SPL.

Each application domain or even each application scenario has demands for specific tests to measure *Runtime Properties*. For instance, a DBMS is measured via standard tests like the TPC Benchmark[3] which defines the data to be stored and queries that have to be executed. We consider a benchmark as a client application that uses the derived product and produces an output that can be evaluated by our tool. Another reason for this approach lies in existing functional difference between derived products. Having functionality in a product may require changes in the benchmark, i.e., explicit function calls to enable the new functionality. If the benchmark is static for all products of the SPL the varying functionality cannot be activated. Only adaptable benchmarks allow the correct measurement of *Runtime Properties* of SPLs.

Omitting SPL products to reduce the amount of performance measurements can lead to false interpolated values because of unpredictable feature interactions. For example, consider two sorting algorithms that speed up a program because they use large main memory space. Although, both of them increase the performance in isolation and they have no direct interactions, in combination they may degrade the performance because both share the same (too small) main memory. This shows that even features with no functional dependencies can have a large influence on a *Runtime Property* if used in combination.

[3]`http://www.tpc.org`

4 Optimization Process

For our optimization process, we adapt the concept of the staged product derivation process [12]. This means we guide a user stepwise through the configuration process. In each step the number of possible configurations can be decreased. The first stage includes a selection of features based on functional requirements, e.g., the user wants *Transaction* and *Sorting*. Existing approaches only focus on this stage. Already at this point, we can give hints for configuring non-functional properties (*Direct Assigned Properties*). The next stages are part of the optimization non-functional properties and based on the pre-configuration of the first stage which consists of configured features that have to appear in a product. The optimization task is to find the best implementations for these selected features using a given objective function. In the following process, we use non-functional constraints to restrict the number of products and this objective function to optimized a certain non-functional property. For example, a stakeholder wants to derive the product which maximizes the performance while the cyclomatic complexity is less than 25 and the binary size is smaller than 300 kBytes.

To derive an optimized product in reasonable time, we developed several strategies to reduce the complexity of that process. In literature, most approaches are based on *constraint satisfaction problem (CSP)* solver [7]. We developed an algorithm that includes several optimization strategies, e.g., using developer knowledge.

Figure 2 presents an overview of our optimization process. Non-functional properties of the class *Direct Assigned Properties* are directly mapped to features. In our example of the Berkeley DB SPL, we have to consider about 400.000 possible products. In the first configuration stage (feature selection), the number of possible products can be reduced to several thousand because only these products provide the needed functionality. The number of products depends on the manual selection of functional properties. Members of class *Inferred Properties* are measured before product derivation and are stored in the PLM. In the second stage, product variants can be excluded because of given non-functional constraints like a restricted binary size. This reduction is possible because we are able to compute the resulting values for the *Inferred Properties* in advance. In our case studies, only a small number usually lower than one hundred possible products remain. Because this may be still too large for a complete measurement, we sort the configuration for the last stage to measure required *Runtime Properties* of the probably best configuration first. These measurements allows us to compute final result of the objective function. This step is repeated with a slightly changed product that may improve the result. Using this process we will find a local optimum. If the number of remaining products allows its complete measurement we will find the global optimum. This process is repeated until a given time interval exceeds or a user stops the task.

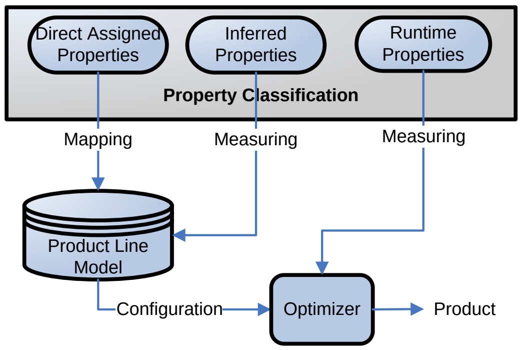


Figure 2. Optimization and Measurement Chain.

5 Evaluation

We evaluate the derivation process to demonstrate the applicability of our measurements and the applicability of the optimization[4]. We use three different SPLs: LinkedList, FAME-DBMS, and Berkeley DB. First, the very small *LinkedList* product line implements a linked list with alternative sorting and traversing algorithms. We use this SPL because its small size and low number of products allows building and comparing all variants with the calculated values. Second, the *FAME-DBMS* SPL prototype implements a flexible, tailor-made DBMS for usage in embedded systems like sensors. The third SPL is the refactored version of *Berkeley DB* [28]. The number of features, variants, and lines of code (LOC) are given in Table 3.

Optimization Process. We measured these three SPLs to give an impression how much time is needed to measure non-functional properties and to perform the whole derivation process. Berkeley DB and FAME-DBMS are chosen because we want to present evaluation results for SPLs that are used in real environments.

Our first demonstration shows how the reduction of the number of possible products is applicable in realistic scenarios. The first scenario is located in resource constrained environments. In these environments the cost of an embedded system strongly depends on the memory that is required. Even a small reduction of required memory can lead to significant savings in mass production. Usually, a stakeholder defines an objective function that may minimize the production cost of an embedded device. For this scenario, a simplified objective function can be:

$$min\{BinarySize_i\}$$

The binary size is given in Bytes and i represents a product. The second scenario maximizes the maintainability in order to derive an evolvable product while having a binary size and performance constraint:

$$min\{CyclomaticComplexity_i \mid BinarySize < 150KB; Performance >= 20T/s\}.$$

The first stage of reducing the search space for an optimal product is the functional selection of features which is the same for both scenarios. Obviously, this depends on functional requirements of a stakeholder. We randomly select features in order to simulate such requirements for both scenario. For each SPL a configuration was chosen which is shown in Figure 3 (Txn_BDB, Btree_FAME, and Sorting_LL). This random configuration is the result after the first stage. Table 2 depicts the results after each stage. Because of domain constraints and the hierarchical arrangement of features, the first stage has usually the largest impact on the reduction. However, this reduction is not enough to measure *Runtime Properties*. Therefore, we use in the second stage the given non-functional constraints of our second scenario (without non-functional constraint like the scenario the number stays constant). We use the binary size constraint of the second scenario because only this property can be evaluated in advance. This reduces the number of products for the second scenario as shown in Table 2. This means, that such constraints can have a large impact on the reduction but can also have no impact for too weak defined constraints. This depends on the constraint itself and on the products that can be generated by an SPL. The second stage already provides the best product for the first scenario (lowest binary size), thus no runtime measurements are needed. However, in the second scenario the runtime property performance is involved. We are searching for the lowest cyclomatic complexity for a given performance constraint. We can already create a ranking of products based on cyclomatic complexity in the second stage, but we need runtime measures to determine whether they meet the performance constraints. For Berkeley DB the first product fulfills the constraint and for the other products we only need small number of measurements (see Table 2).

Time for Measurements. The one-time measurement of the properties maintainability and binary size takes altogether about 35 minutes including all SPLs. The cyclomatic complexity measurement takes only a few seconds but the manual allocation to features requires a few minutes (see Table 3). The measurement of the binary size includes the compilation of the SPL with all features and code units and

[4]Our evaluations are made on a Pentium 4, 3.00 GHz computer with 2 GB RAM. The installed operation system was Microsoft Windows XP SP2.

	Txn_BDB	Btree_FAME	Sorting_LL
Max Variants	400.000	320	480
Stage 1	2000	48	120
Stage 2	10	22	40
Stage 3	1	5	3

Table 2. Reducing the number of products during staged product derivation.

automatic allocation of the binary size of a method to a feature. The compilation requires the largest amount of time. The automatic allocation requires less than one minute for the LinkedList and FAME-DBMS. Performing this task for the larger Berkeley DB SPL takes 3 minutes. These times (see Table 3) are within a reasonable range, considering that the entire SPL is measured not every single variant. The whole derivation process requires for 5 measurements of R*untime Properties* for the Berkeley DB SPL about 50 minutes. Because of faster compilation the LinkedList takes only 10 minutes for the whole process and FAME-DBMS requires 35 minutes.

Accuracy of Measurements. The accuracy of the measurement is very important to retrieve valid and optimized products. First, cyclomatic complexity is already a metric aggregated from measurements of individual methods. Therefore a measurement per feature and aggregation per product is accurate, as we could also confirm in the generated variants.

Second, the performance is measured for each product in isolation which means that this non-functional property is as accurate as the benchmark is.

Finally, the computation of the binary size of a product is based on values that can change in dependency to the compiler and the product we want to generate. Therefore, we have to consider this inaccuracy of the binary size calculation introduced by compiler optimizations like *function inlining*. To evaluate the accuracy of our approach we derived some sample products to measure the divergence between the calculated binary size and the real binary size including compiler optimizations. Although, the results depend on the implementation of the SPL we found that the divergence is less than 10 percent. Figure 3 presents binary size evaluations of two product variants for each SPL. We measured a minimal version that includes only mandatory features and a large version with more than 10 additional features. For the base (minimal configuration) version of the LinkedList SPL and FAME-DBMS SPL the divergence is less than one percent. Berkeley DB has a higher fault percentage because of a large number of small methods that could be optimized by the compiler. By introducing additional features the divergence of the computed result decreases for Berkeley DB reasoned by functions that cannot be inlined. The error of the LinkedList in the product with additional sorting is reasoned by the small amount of code per feature. This was often be inlined in different functions which increases the binary size. This is the only case where the real binary size is larger than the computed binary size and the difference is more than one percent which may lead to measuring *Runtime Properties* of invalid configurations.

Discussion. The main problem of measuring non-functional properties in SPLs and optimizing products for non-functional properties is the large number of possible products. The classification we have shown in Section 3 allows to measure some properties without having this problem. However, for *Runtime Properties* there is no solution until now that can provide acceptable measurements regarding to time needed for measurement and accuracy of the results. Thus, we shifted the measurement of *Runtime Properties* to the derivation process because this enables us to measure only a small subset of all possible products, i.e., only these products that are relevant for a stakeholder. To reduce the number of products we extended the idea of a staged product derivation [12]. This reduction strongly depends on the non-functional constraints and objective function given by the stakeholder. If only *Runtime Properties* are constrained or have to be optimized we cannot significantly reduce the search space. This means, that the derived products may not be optimal and the needed amount of time for measuring *Runtime Properties* may not be applicable for this case. However, we believe that in most cases our approach enables stakeholders to derive products in an reasonable time that fulfill desired non-functional properties.

6 Related Work

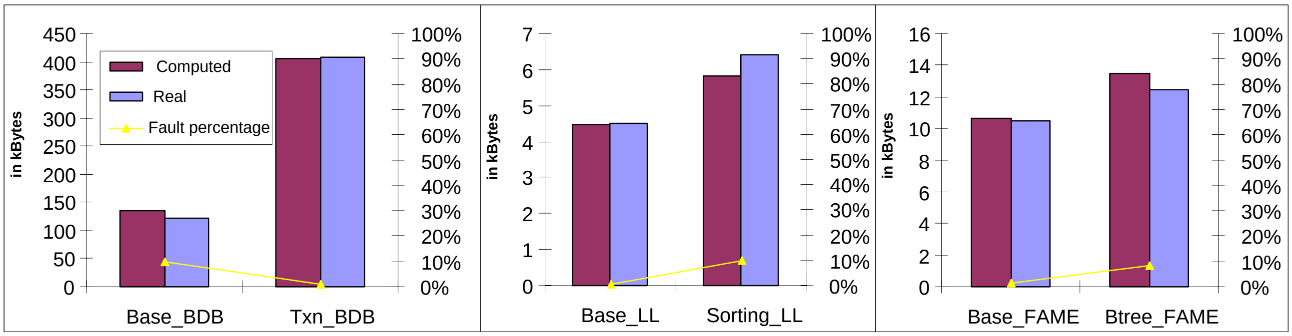
There are a number of approaches that ease the product derivation process [33, 29, 8, 35]. These tools guide stakeholders through the selection of features with special visualization techniques. However, these approaches concentrate only on functional properties of a product and their dependencies. The measurement of non-functional properties and the configuration of those properties are not addressed.

Some approaches propose techniques on automated reasoning on feature models [7, 6] or SPLs in general [35]. Benavides et al. [7] integrate non-functional properties inside the product derivation process. However, their work leaves the measurement of the values of these properties as an open problem.

Only a few approaches adapted measurements to SPLs. Either they define the measurements only from a business

SPL	Features	Variants	LOC	Time for measuring (min) Complexity	Binary Size	Avg. Performance (one product)
LinkedList	22	480	886	3	2	<1
FAME-DBMS	21	320	8602	3	6	4
Berkeley DB	36	ca. 400.000	141.198	10	11	9

Table 3. Time spent for measuring the maintainability and the binary size of three SPLs in minutes.



Configuration	Number of Features	Short Description
Base_LL	5	Minimal product of a *LinkedList* SPL
Sorting_LL	12	*Sorting* and *Traversing* features
Base_FAME	15	Minimal in-memory FAME-DBMS version
Btree_FAME	17	*Read* and *Write* support for storage and *Btree* index
Base_BDB	7	Minimal *BerkeleyDB* configuration
Txn_BDB	30	*Transaction*, *Logging*, *Btree*, *Upgrade*, and *Recovery* features

Figure 3. Comparison of computed and real binary size for 6 configurations.

view to evaluate the development effort [13] or they express only the complexity (in terms of variation points) of the whole product line [21]. An approach close to our work is the measurement of the binary size of an aspect-oriented SPL [17]. Aspects are compiled in distinct files and their size is measured. The binary size of different products can be calculated. However, the approach does not consider other properties or the exponential number of products that occur during the derivation process. The configuration of non-functional properties in SPLs is also addressed by Sincero et al. [31]. This approach tries to overcome the problem of the large number of products by storing the non-functional properties of each derived product in a repository. In addition, automatically generated products further enrich the repository. In contrast, we store non *Runtime Properties* inside a feature model assigned to features. With this information we are able to reduce the number of products and have to measure only potential good candidates.

7 Summary and Future Work

In this paper we presented an approach for measuring non-functional properties in *software product lines (SPLs)* to allow an automatic configuration of code units. We have addressed the problems of measuring diverse non-functional properties by proposing a classification. For each class we presented examples and showed how these can be measured. We proposed several techniques to reduce the number of possible products by sorting and excluding product candidates because of a staged configuring. In an evaluation, we have shown that our approach can significantly reduce the product derivation complexity and the effort to obtain a product including desired non-functional properties.

In further work, we will extend our approach to dynamically evaluate runtime properties and decrease the error rate of the binary size.

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