t-wise Coverage by Uniform Sampling

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ABSTRACT

Efficiently testing large configuration spaces of *Software Product Lines* (SPLs) needs a sampling algorithm that is both scalable and provides good t-wise coverage. The 2019 SPLC Sampling Challenge provides large real-world feature models and asks for a t-wise sampling algorithm that can work for those models.

We evaluated t-wise coverage by *uniform sampling* ($\mathbb{US}$) the configurations of one of the provided feature models. $\mathbb{US}$ means that every (legal) configuration is equally likely to be selected. $\mathbb{US}$ yields statistically representative samples of a configuration space and can be used as a baseline to compare other sampling algorithms.

We used existing algorithm called Smarch to uniformly sample SPL configurations. While uniform sampling alone was not enough to produce 100% 1-wise and 2-wise coverage, we used standard probabilistic analysis to explain our experimental results and to conjecture how uniform sampling may enhance the scalability of existing t-wise sampling algorithms.

CCS CONCEPTS

• **Software and its engineering** → **Software product lines**; • **Theory of computation** → **Automated reasoning**.

KEYWORDS

software product lines, t-wise coverage, uniform sampling.

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1 INTRODUCTION

Software Product Lines (SPLs) are highly configurable. Building blocks of SPL products are *features* that are increments of product functionality. Each product of an SPL is defined by a unique set of features called a *configuration*. A *feature model* declares each feature and constraints among features, so that a user can identify legal configurations with desired feature combinations [4]. As the number of features increase, the size of the *configuration space*, which is the set of all possible configurations, grows exponentially.

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A large configuration space could have over a trillion ($>10^{12}$) configurations and is a challenge for testing, as testing every configuration is infeasible. Instead, prior work produced a small set of configurations to test selected features and their interactions. The aim is to get a 'high' t-wise coverage, ideally meaning 100% of *all* combinations of t features are covered by at least one configuration of the set. Achieving 100% can be infeasible for large spaces.[1] Common values for t include feature-wise (t=1), pair-wise (t=2), and three-wise coverage (t=3).

Different approaches start with a feature model and derive samples for t-wise coverage [1, 2, 6, 9, 10]. However, they do not scale well for many features and complex constraints, which limited their applicability to the real-world SPLs. Thus, the proposed Challenge [16] provides large real-world feature models and asks for a sampling algorithm that can generate configuration sets with good t-wise coverage for those models.

We explore t-wise coverage using *uniform sampling* ($\mathbb{US}$) in this paper. $\mathbb{US}$ ensures that all configurations in a configuration space have equal probability of being selected, yielding a *statistically representative sample* of the space. $\mathbb{US}$ can be used as a baseline against which other sampling algorithms can compare as a benchmark [13].

Despite its utility, $\mathbb{US}$ for large SPLs was considered infeasible until recently [11, 13]. Prior work tried different methods to make sampling as random as possible, but none achieved $\mathbb{US}$ for large SPLs. We use a recently developed algorithm called Smarch [8], the first to perform $\mathbb{US}$ of configuration spaces of size 10^{245}. Smarch utilizes a #SAT solver, which counts the number of solutions to a propositional formula [15]. We believe we are the first to explore t-wise coverage of $\mathbb{US}$ with probabilistic analyses to explain its coverage results.

Our contributions to the 2019 SPLC Sampling Challengeare:

- Demonstration of t-wise coverage that can be achieved by $\mathbb{US}$; and
- Probabilistic analysis of configuration spaces that predicts the t-wise coverage by $\mathbb{US}$ and that may be useful for developing a practical t-wise sampling algorithm.

2 SMARCH: A $\mathbb{US}$ ALGORITHM

Smarch [8] is a $\mathbb{US}$ algorithm for SPLs based on a #SAT solver. Let ϕ be the propositional formula of a feature model [3]. A #SAT solver can count the number of configurations in ϕ's configuration space, namely $|\phi|$. (Each solution to ϕ is a configuration, and each configuration is a solution to ϕ). A #SAT solver extends a satisfiability solver by associating the number of solutions with each truth assignment [5]. Smarch uses sharpSAT [15], a state-of-the-art #SAT solver.

[1] Section 4 shows that uniform sampling alone will not provide 100% coverage unless the sample set is approximately the size of the configuration space.

Here is how Smarch achieves $\mathbb{US}$: A uniform random number generator can select an integer r in the range $[1..|\phi|]$. Smarch creates a one-to-one mapping that converts r into a unique configuration, so that $\mathbb{US}$ of range $[1..|\phi|]$ leads to $\mathbb{US}$ of configurations.

Smarch recursively partitions ϕ by a fixed order of variables to create a one-to-one mapping. A variable $v \in \phi$ partitions ϕ into disjoint spaces $(\phi \land \neg v)$ and $(\phi \land v)$. #SAT can compute the number of solutions for each space, i.e., $|\phi \land \neg v|$ and $|\phi \land v|$ respectively.

Then, for a random number $r \in [1..|\phi|]$, if $r \leq |\phi \land \neg v|$ the $(\phi \land \neg v)$ space is selected for recursive partitioning, otherwise $(\phi \land v)$ is selected and $|\phi \land \neg v|$ is subtracted from r to adjust the search in $(\phi \land v)$. This process is repeated for the next variable in ϕ, until all variables are considered and a unique configuration has been determined.

Documenting scalability of Smarch and #SAT is beyond the scope of this paper – and is the subject of on-going work. Evidence in [8] reports Smarch is able to $\mathbb{US}$ configuration spaces of size $O(10^{248})$ whereas the nearest $\mathbb{US}$ competitor's largest space is $O(10^{13})$.

3 EVALUATION

3.1 Experimental Set-Up

Among the feature models provided in the Challenge, we used 'FinancialServices01' version '2018-05-09'. This feature model was given in FeatureIDE format [14], so we used the functionality of FeatureIDE to generate its propositional formula as a dimacs file. This file has 771 variables and 7,241 clauses. The size of the configuration space was determined to be $9.7 \cdot 10^{14}$, computed in a mere 46 milliseconds by sharpSAT [15].

We evaluated t-wise coverage for t=1 and t=2 and did the following to find valid combinations:

(1) We derived a list of feature selections. With 771 features, there are $771 \cdot 2 = 1{,}542$ possible selections since we consider both a feature and its negation;

(2) We derived all possible 1-wise and 2-wise combinations from this list. 1-wise yields $\binom{1542}{1} = 1542$ combinations and 2-wise yields $\binom{1542}{2} = 1{,}188{,}111$; and

(3) We filtered out invalid combinations using a SAT solver. If a combination is valid, the conjunction of the combination and the feature model should be satisfiable. For example, for a feature f, a 2-wise combination $(f, \neg f)$ is invalid as these selections conflict with each other.

For 1-wise, 1,518 valid combinations were found (some features were mandatory). For 2-wise, 914,537 valid combinations were found.

We used Smarch to produce a $\mathbb{US}$ set $\mathbb{S}_n$ of n configurations.We have no idea what fraction of the valid combinations (computed above) are covered by $\mathbb{S}_n$. So we varied n to observe the results of increasing larger sets, using n={5, 10, 20, 30, 40, 50, 100, 200, 300, 400, 500, 1000, 1518}. Then, for each set $\mathbb{S}_n$, we measured [2]:

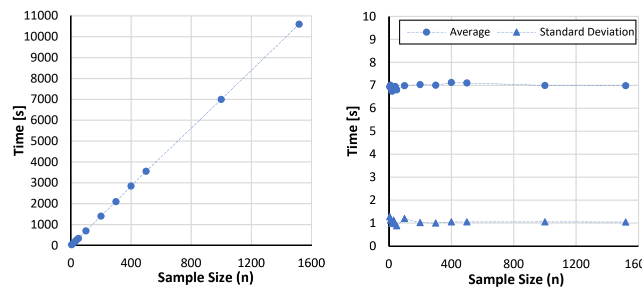
- **Time taken to sample n configurations**, measured by the Linux '`time`' tool;
- **Time taken to sample a configuration**, measured for each sample by Smarch;
- **Maximum memory used during sampling**, measured by the Linux '`/usr/bin/time -v`' command; and
- **t-wise coverage for t=1 and t=2**, measured as the percentage of t-wise combinations covered in $\mathbb{S}_n$.

We conducted our evaluation on an Intel i7-6700@3.4Ghz Ubuntu 16.04 machine with 16GB of RAM. All the code and data for the evaluation are available at: *https://github.com/jeho-oh/Smarch_t_wise.*

3.2 Experimental Results

Fig. 1a shows the total sampling time and Fig. 1b the time per sample. The X-axis is the number of samples (n) and the Y-axis is the time in seconds. We observed:

- Total sampling time increases linearly with n; and
- For all n, the average sampling time for a configuration was approximately 7 seconds, with standard deviation of 1 second. For all samples, the maximum sampling time was 10.1 seconds and the minimum was 3.5 seconds.
- The number of samples taken did not affect the time to sample a configuration.



(a) Total sample time (b) Time per sample

Figure 1: Sampling time.

Fig. 2 shows the maximum memory usage of Smarch, where the X-axis is the number of samples (n) and the Y-axis is the memory size in megabytes. We observed:

- Maximum memory usage was stable, between 16.8MB and 17.1MB for all n; and
- Sampling more configurations did not increase the maximum memory usage.

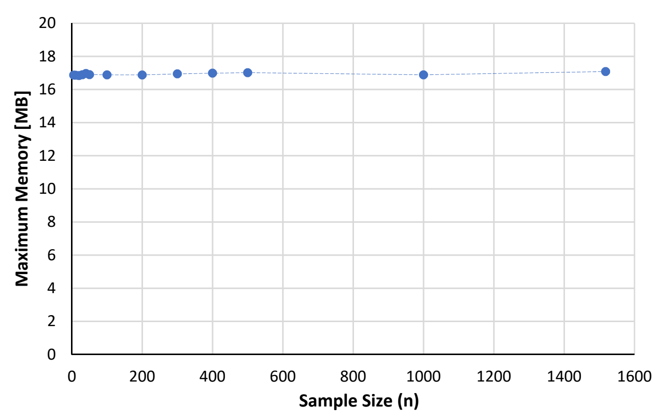


Figure 2: Maximum memory usage.

Fig. 3 shows the t-wise coverage result, where the X-axis is the number of samples (n) and Y-axis is the percentage of the coverage.

[2] The Challenge [16] explicitly requests sampling time and memory measurements.

Plots with different color indicates the results for different t. We observed:

- For all values of n, coverage for t=1 was higher than t=2;
- For $\mathbb{S}_5$, more than half of the feature combinations were covered for t=1 and over 35% for t=2;
- For both t=1 and t=2, larger n yielded better coverage. With 1,518 samples, coverage for t=1 was 61.7% and t=2 was 47.6%;
- The difference in coverage between n=5 and n=1, 518 was surprisingly small. For t=1, the difference was 6.4%. For t=2, the difference was 9.4%; and
- Although samples are expected to be statistically representative of the configuration space, their t-wise coverages seemed low. Both coverages improved imperceptibly for $n \geq 200$. Why this is so is explained in the next section.

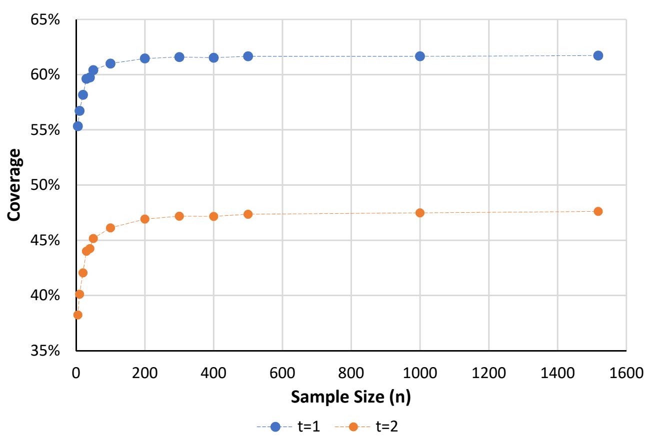


Figure 3: *t*-wise coverage.

We conclude that although $\mathbb{US}$ is feasible with Smarch, $\mathbb{US}$ alone is not enough to produce a 100% t-wise coverage.

4 ANALYSIS

$\mathbb{US}$ allows us to apply standard statistical analysis to explain our experimental results [7].

Let c denote a valid t-wise combination for a given t. Let v_c denote the fraction of all valid configurations that have c in the configuration space. Since every configuration has an equal probability of being selected by $\mathbb{US}$, the probability that a sample will have c is v_c.

v_c can vary widely for different c because constraints among features may make certain combinations less frequent than others. A mandatory feature has v_c=1 because it appears in all configurations. A feature with no constraints has v_c=0.5; it can be freely enabled and disabled, making it appear in half of the valid configurations.

v_c can be computed by a #SAT solver. Let ϕ be the propositional formula of an SPL's feature model. Let ϕ_c be the propositional formula of the conjunction of c's features. We can use a #SAT solver to compute v_c as:

$$v_c = \frac{|\phi_c|}{|\phi|} \tag{1}$$

The probability $p(c, n)$ that at least one of n samples includes combination c is:

$$p(c, n) = 1 - (1 - v_c)^n \tag{2}$$

where the more samples taken, the higher the probability we encounter combination c. The value of $p(c, n)$ largely depends on how often this combination appears in the configuration space, i.e., v_c.

In our experiments of the previous section, we discovered:

- 61.5% of all 1-wise combinations have a ratio v_c>0.9. Even with the minimum number of samples we used in the evaluation (n=5), these combinations have more than 0.99 probability of being encountered in n=5 samples; and
- 38.8% of the 1-wise combinations have a ratio of v_c<0.0001. Even with the maximum number of samples we used in the evaluation (n=1815), they have less than 0.15 probability of being encountered in n=1815 samples.

We can use $p(c, n)$ to predict t-wise coverage. Let $\mathbb{C}_t$ denote the set of all valid t-wise combinations, where $|\mathbb{C}_t|$ is the number of combinations in $\mathbb{C}_t$. The estimated t-wise coverage $E(\mathbb{C}_t, n)$ for a given t, n is:

$$E(\mathbb{C}_t, n) = \frac{1}{|\mathbb{C}_t|} \sum_{c \in \mathbb{C}_t} p(c, n) = \frac{1}{|\mathbb{C}_t|} \sum_{c \in \mathbb{C}_t} (1 - (1 - v_c)^n) \tag{3}$$

Fig. 4 uses (**blue**) X markers to plot $E(\mathbb{C}_1, n)$ and (**brown**) X markers for $E(\mathbb{C}_2, n)$ with our experimental results (• for t=1 and • for t=2) overlaid. Eqn. (3) accurately predicts the results of our experiments and also explains why the coverage of t=1 is higher than that for t=2: there are many 2-way feature combinations (c_{ij}) that are much less likely than any 1-way combination (c_k), meaning $v_{c_k} \gg v_{c_{ij}}$.

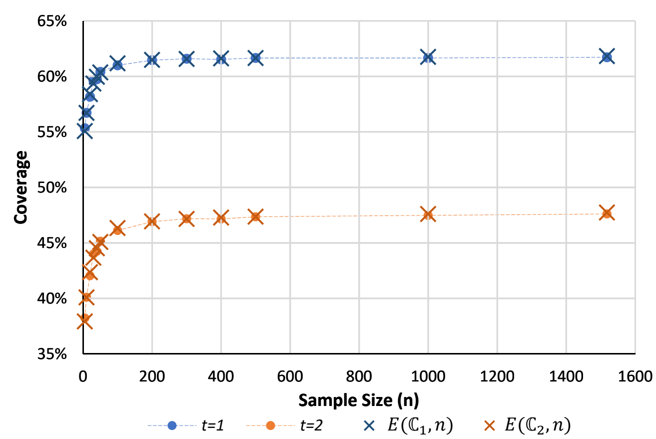


Figure 4: *t*-wise coverage estimation.

It is interesting to explore the relationship between coverage and larger sample set sizes *which are infeasible to explore experimentally*. Fig. 5 shows the estimated t-wise coverage for n up to 10^{14}, which is approximately 10% of the configuration space (*ie.,* 9.7×10^{14}). We observed:

- With 10^{14} samples, more than 99.99% of 1-wise and 2-wise combinations are expected to be covered. Of course, this is almost enumeration; and

- Many combinations will be covered with a small number of samples, over 30% of 2-way combinations are not likely to be covered even with 10^7 samples(!).

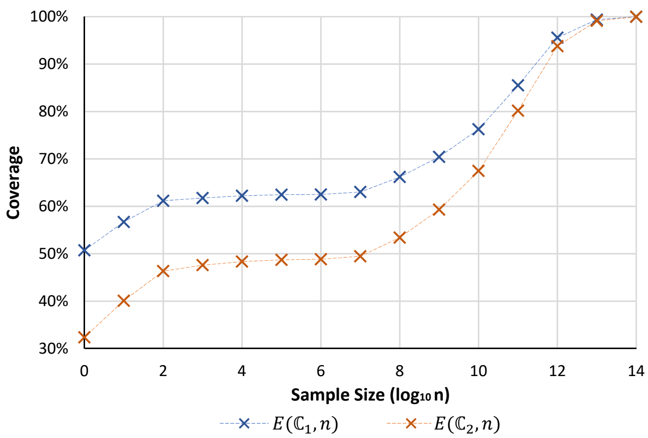


Figure 5: t-wise coverage estimation for large n.

We could accurately predict these results because Smarch can uniform sample from a configuration space and standard probabilistic analyses rely on $\mathbb{US}$ [7].

Our analysis suggests possible enhancements to existing t-wise approaches. Once v_c values are known, we can determine which combinations can be covered by a small number of $\mathbb{US}$s. Then, for combinations that are unlikely to be found by $\mathbb{US}$, we may either: 1) constrict the configuration space with constraints to (recursively) sample configuration sub-space of interest [12] or 2) use existing approaches that do not rely on $\mathbb{US}$. As sampling with many features limits the scalability of existing approaches, $\mathbb{US}$ may improve sampling scalability by reducing the features to consider. An equally important issue is to define a reasonable t-wise coverage (percentage) for large configuration spaces (other than 100%) for practitioners to use.

5 CONCLUSIONS AND FUTURE WORK

As $\mathbb{US}$ of configurations was considered infeasible, probabilistic analyses of a configuration space based on $\mathbb{US}$ was unexplored or considered unexplorable. We used a recently developed algorithm, Smarch [8], to $\mathbb{US}$ configurations of a configuration space. We also derived probabilistic models to explain Smarch results. We showed:

- $\mathbb{US}$ alone is ***not*** enough to produce 100% t-wise coverage; and
- Distribution of v_c can be used to predict the t-wise coverage of $\mathbb{US}$.

Our work opens new possibilities on analyzing an SPL configuration space and deriving samples for testing. As $\mathbb{US}$ produces statistically representative samples of a configuration space, it may be possible to utilize the information from samples to improve the efficiency of existing approaches. As a future work, we plan to:

- Analyze other systems to validate and expand our insights on probabilistic analyses;
- Derive an algorithm utilizing $\mathbb{US}$ for t-wise coverage; and
- Enhance the performance of the Smarch algorithm.

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