

Automatic Generation of Tests with Constraint Programming

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Charles-Antoine Leger - Rania Saadi - Armand Thibaudon

charles-antoine.leger@epita.fr rania.saadi@epita.fr armand.thibaudon@epita.fr

Classic Example

Let's consider a Python function with **10 parameters** where each of theses parameters has between **3 and 10 possible values**:

```
def complex(
   param1, param2, param3, param4, param5, param6, param7, param8, param9, param10
):
```

- How many possible factor combinations?
- Our goal is to reduce this number while maintaining a high test suite coverage

Introduction

Generate, automatically, tests for a python **function** based on its **factors** (parameters) and their **factor levels** (possible values)

Main challenges:

- Combinatorial Explosion: with a high number of parameters and large domains (high factor levels), the test suite can become too large, leading to long execution times
- Avoid Redundancy: many combinations may be redundant or provide little additional coverage
- Ensure Sufficient Code Coverage: the generated test suite must provide strong coverage to ensure code safety and reliability

Algorithm

- The algorithm is implemented in python
- Z3 package for handling constraints solving
- coverage package to compute coverage of tests
- MCP for LLM prompting



Figure 1: Presented algorithm pipeline

Code Analysis

Our aim:

- To determine which values of a parameter meaningfully affect the function's behavior.
- To avoid testing redundant or equivalent inputs.
- Ideally, to do so automatically.

Let's begin by identifying the **parameters** and their respective **domains**:

- Static analysis
- LLM

```
def is_positive(n):
    if n > 0:
        return True
    else:
        return False
```

t-wise Testing

What is t-wise testing?

- Also called Combinatorial Interaction Testing (CIT).
- A black-box testing approach that focuses on interactions between input parameters.
- 't' represents the **interaction strength** e.g., 2-wise tests all pairs, 3-wise tests all triples, etc.

Why is it pertinent?

- Efficient fault detection: Many software faults are triggered by specific combinations of inputs. t-wise testing detects these without exhaustive testing.
- Scalable sampling strategy: Instead of checking every possible combination (which grows exponentially),
 it ensures coverage of smaller but meaningful sets of interactions using covering arrays.
- **Proven effectiveness**: Studies (e.g., Kuhn et al.) show high fault detection rates with relatively low test suite sizes.

Proven Effectiveness of t-wise Testing

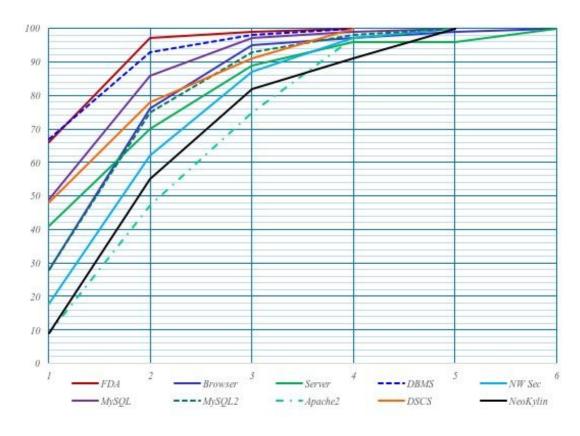


Figure 2: Cumulative proportion of faults¹

t-wise Testing Matrix

- Let's imagine a function that takes three parameters, each with the following domain: [0, 1]
- Our goal is to construct the corresponding pairwise (2-wise) testing matrix for this function

X	Y	Z
0	1	0
1	0	1
0	0	0
1	1	0
0	1	1

Figure 3: t-wise combination matrix for t = 2

Initial Tests Generation

From each parameter and its domain, we generate all possible combinations to serve as inputs
 for the function

Once this is done, we randomly sample from these combinations to obtain a representative subset

Correlation Matrix

- To choose t for a test case, we rely on the correlation coefficient
- It gives an idea on how much two or more parameter are related

$$Corr(X, Y) = \frac{I_{XY}}{I_X * I_Y}$$

Correlation is computed from the impact of parameters on the code coverage

$$I_p = C_p^{\max} - C_p^{\min}$$

It gives us the correlation matrix

Parameter	P_1	P_2		P_n
$\overline{P_1}$	_	$Corr(P_1, P_2)$		$Corr(P_1, P_n)$
P_2	$Corr(P_2, P_1)$	_		$Corr(P_2, P_n)$
			_	
P_n	$Corr(P_n, P_1)$	$Corr(P_n, P_2)$		_

Table 1: Conceptual model of parameter correlation matrix

Strength Calculation

Parameter	P_1	P_2		P_n
$\overline{P_1}$	_	$Corr(P_1, P_2)$		$Corr(P_1, P_n)$
P_2	$Corr(P_2, P_1)$	_		$Corr(P_2, P_n)$
			—	
P_n	$Corr(P_n, P_1)$	$Corr(P_n, P_2)$		<u> </u>

- To choose a the number of classes of strength (t) for a pair, we calculate the variance of the correlation (V) and the range of the correlation (R)
- The number of classes of strength (S) determines the number of correlation thresholds
 (T); we chose to have equally spaced thresholds such that:

With number of parameters N N >= 2 and $i_0 = 1$, we define:

$$S = max(V(N-1), 2)$$

$$T_i = i * (R/S)$$

Results - 1

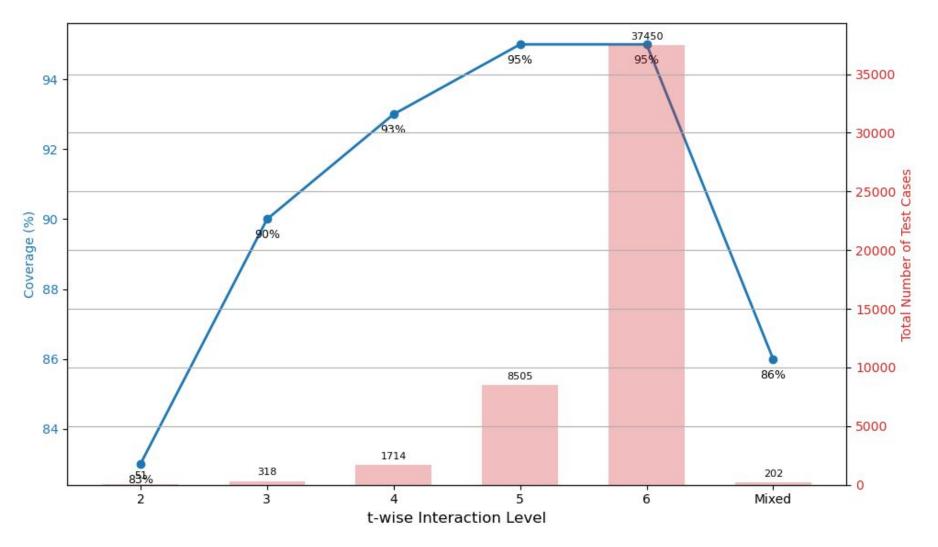


Figure 4: Test Coverage per t-wise Interaction Level - 1

Results - 2

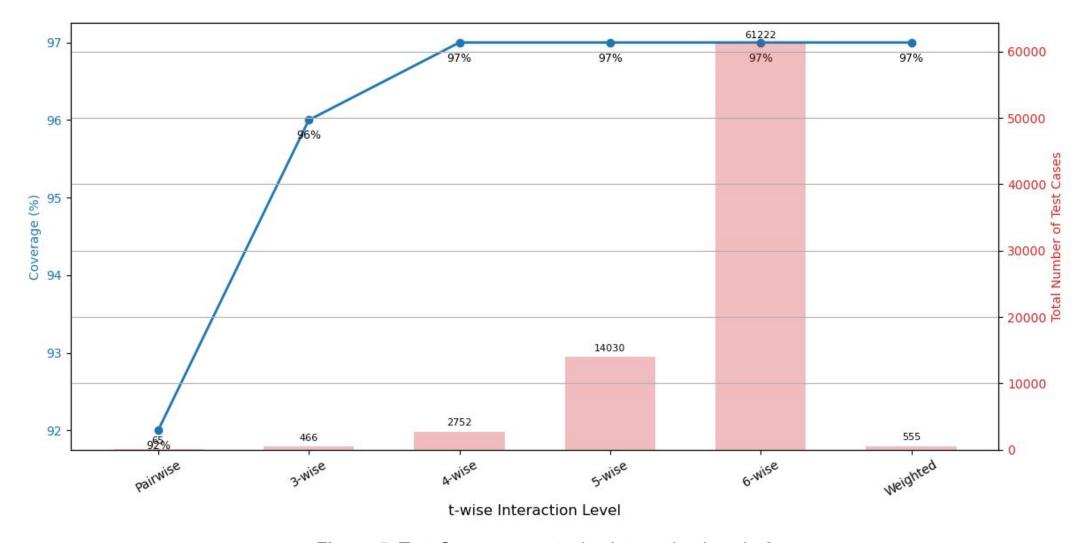


Figure 5: Test Coverage per t-wise Interaction Level - 2

Live Demo

Let's try it out!

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