Search-Based Software Testing Based on Information Theory

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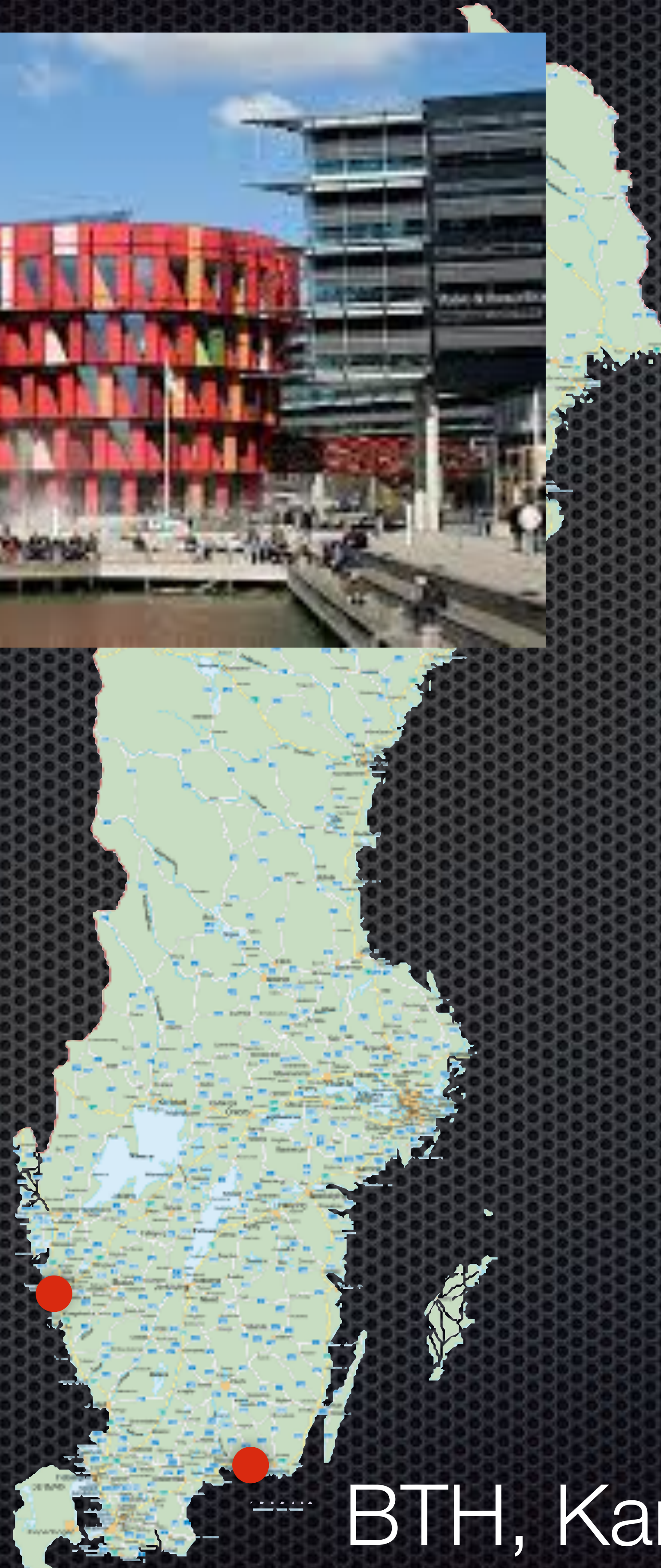
Göteborg
BTH, Karlskrona



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ICSE 40TH INTERNATIONAL CONFERENCE ON SOFTWARE ENGINEERING

MAY 27 - JUNE 3 2018
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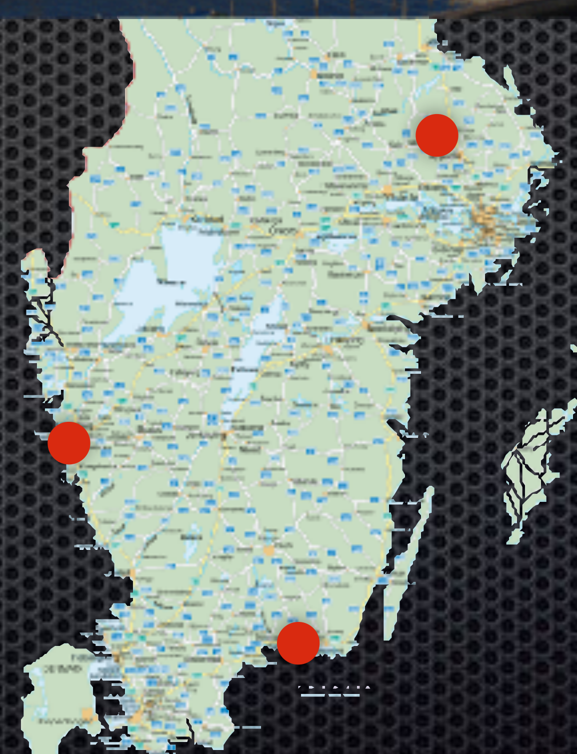
MDH, Västerås



MDH, Västerås

Testing still (mainly) based on intuition & heuristics

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To formalise, analyse, automate etc we need to **quantify**!

There are MANY distance functions

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A **metric** on a set X is a function (called the *distance function* or simply **distance**)

$$d : X \times X \to [0,\infty),$$

where $[0,\infty)$ is the set of **non-negative** real numbers (because distance can't be negative so we can't use **R**), and for all x, y, z in X, the following conditions are satisfied:

1. $d(x,y) \geq 0$ — non-negativity or separation axiom
2. $d(x,y) = 0 \Leftrightarrow x = y$ — identity of indiscernibles
3. $d(x,y) = d(y,x)$ — symmetry
4. $d(x,z) \leq d(x,y) + d(y,z)$ — subadditivity or triangle inequality

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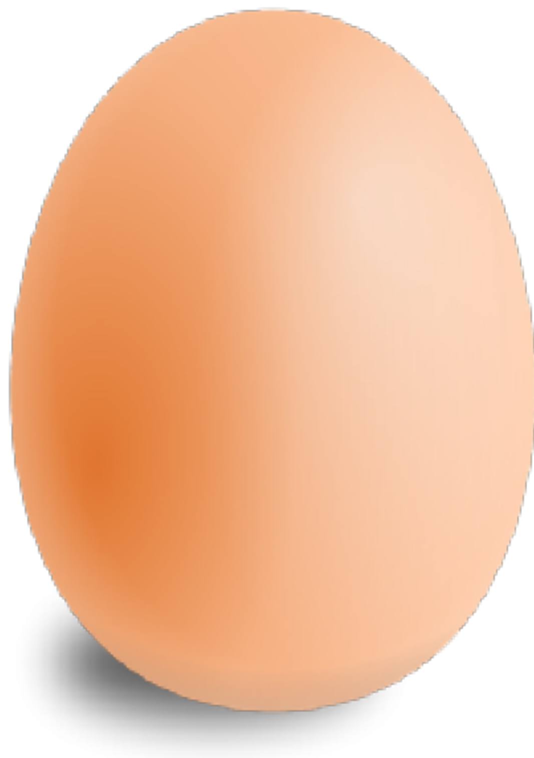
$d_1($  ,  $) = num$

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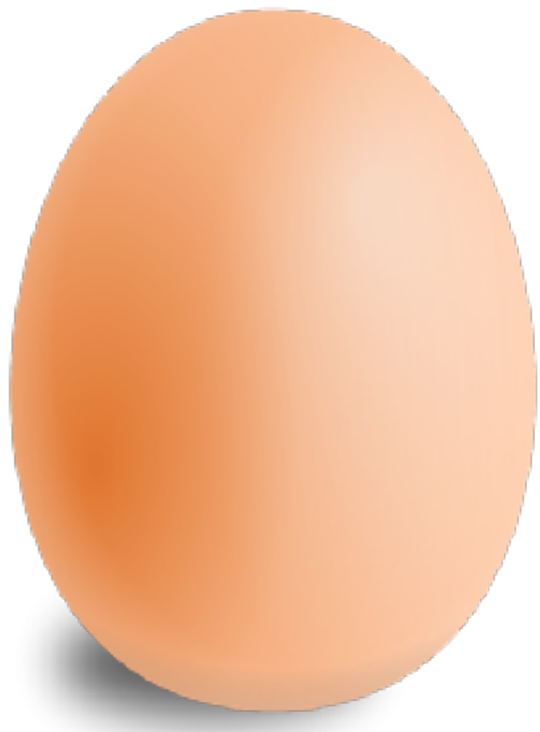
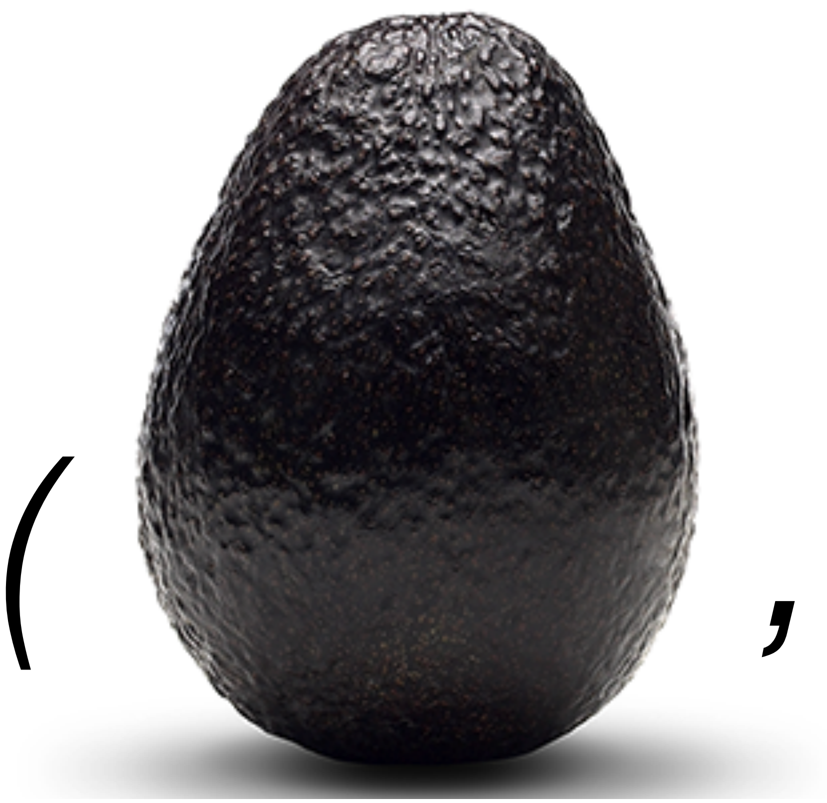
$d_1($  ,  $) = num$

$d_2($  ,  $) = num$

They are (always) pair-wise and/or data-dependent

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- And shows that test sets selected by it
  - **<u>increases code and fault coverage</u>**

So what is Information Theory?

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Reprinted with corrections from *The Bell System Technical Journal*,
Vol. 27, pp. 379–423, 623–656, July, October, 1948.

A Mathematical Theory of Communication

By C. E. SHANNON

INTRODUCTION

THE recent development of various methods of modulation such as PCM and PPM which exchange bandwidth for signal-to-noise ratio has intensified the interest in a general theory of communication. A basis for such a theory is contained in the important papers of Nyquist[1] and Hartley[2] on this subject. In the present paper we will extend the theory to include a number of new factors, in particular the effect of noise in the channel, and the savings possible due to the statistical structure of the original message and due to the nature of the final destination of the information.

The fundamental problem of communication is that of reproducing at one point either exactly or approximately a message selected at another point. Frequently the messages have *meaning*; that is they refer to or are correlated according to some system with certain physical or conceptual entities. These semantic aspects of communication are irrelevant to the engineering problem. The significant aspect is that the actual message is one *selected from a set* of possible messages. The system must be designed to operate for each possible selection, not just the one which will actually be chosen since this is unknown at the time of design.

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So what is Information Theory?

Application of probability theory & statistics to problems of quantification, storage and communication of information.

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$$S = \log_2 2^N = N = 2$$

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THREE APPROACHES TO THE QUANTITATIVE DEFINITION OF INFORMATION

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Kolmogorov complexity of object x = K(x) = length of shortest program to generate x (given no input)

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We can apply this trick to a large number of theoretical results and formulas and get methods that often works surprisingly well in practice.

Information distance

Information distance

Roughly speaking, two objects are deemed close if we can significantly “compress” one given the information in the other, the idea being that if two pieces are more similar, then we can more succinctly describe one given the other.

Already at ICST 2008 in Lillehammer…

Searching for Cognitively Diverse Tests: Towards Universal Test Diversity Metrics

Robert Feldt, Richard Torkar, Tony Gorschek and Wasif Afzal
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Blekinge Institute of Technology
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Abstract

Search-based software testing (SBST) has shown a potential to decrease cost and increase quality of testing-related software development activities. Research in SBST has so far mainly focused on the search for isolated tests like statement or branch coverage, even though other approaches have been reported [3, 14]. However, only a few studies have used relative fitness functions that compares newly found tests to the ones previously in the test set, to optimize the test set as a whole [2]. This is unfortunate since an optimal set of tests is what is ultimately needed.

Already at ICST 2008 in Lillehammer…

$$\mathrm{NID}(x, y) = \frac{\max\{K(x|y), K(y|x)\}}{\max\{K(x), K(y)\}}$$

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$$\mathbf{NID}(x,y) = \frac{\max\{K(x|y), K(y|x)\}}{\max\{K(x), K(y)\}}$$

Information distance between two strings x & y is the length of the shortest program that outputs x given input y, or that outputs y given input x, whichever is largest

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$$\mathrm{NCD}(x,y) = \frac{C(xy) - \min\{C(x), C(y)\}}{\max\{C(x), C(y)\}}$$

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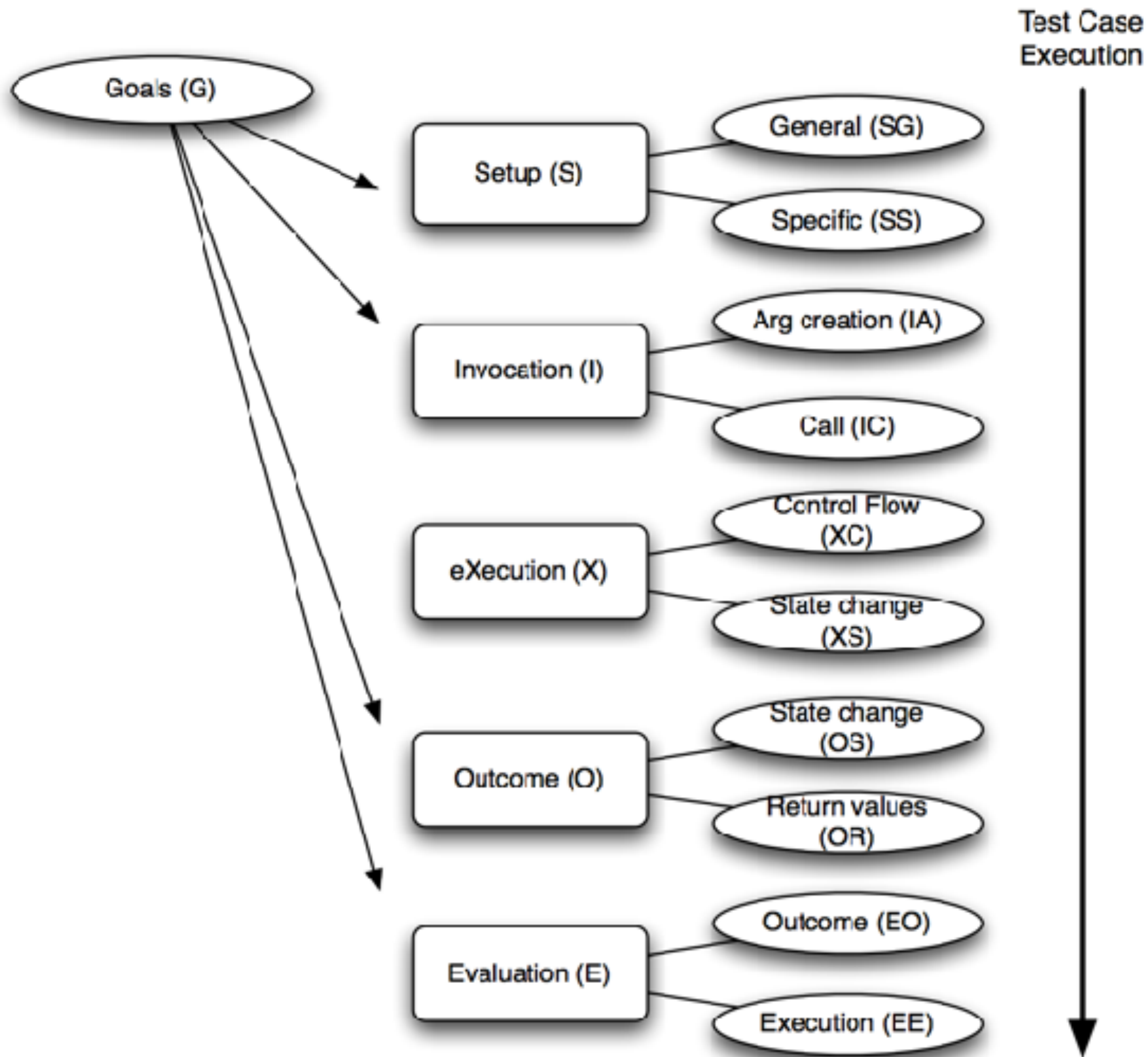
$$\mathrm{NCD}(x, y) = \frac{C(xy) - \min\{C(x), C(y)\}}{\max\{C(x), C(y)\}}$$

where C(s) is length of string s after being compressed
with your favourite compressor
(zlib, bzip2, ppm, blosc, lz4, zstandard, …)

Many sources of test case information



VAriability of Tests (VAT) Model of test information sources/types

Test Set Diameter:

Quantifying the Diversity of Sets of Test Cases

Robert Feldt, Simon Poulding, David Clark, and Shin Yoo

BLEKINGE TEKNISKA HÖGSKOLA · BTH ·
DEPARTMENT OF SOFTWARE ENGINEERING
UCL
KAIST

NCD for multisets (aka “bags”, “lists”, …)

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$$\mathrm{NCD}_1(X) = \frac{C(X) - \min_{x \in X}\{C(x)\}}{\max_{x \in X}\{C(X \setminus \{x\})\}}$$

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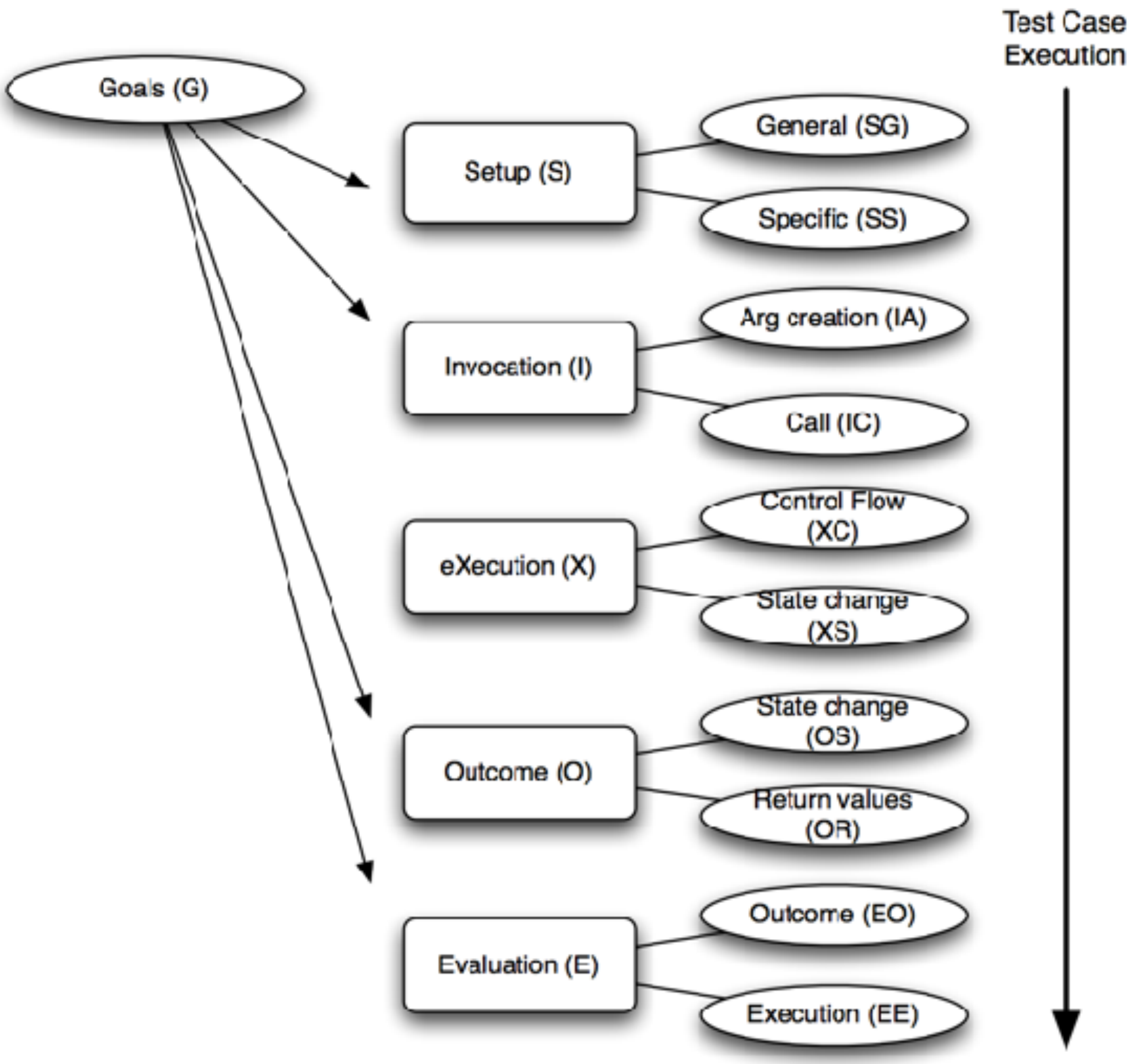
The algorithm starts from the multiset $Y_0 = X = \{x_1, x_2, \ldots, x_n\}$, and proceeds as:

1) Find index i that maximizes $C(Y_k \setminus \{x_i\})$.
2) Let $Y_{k+1} = Y_k \setminus x_i$.
3) Repeat from step 1 until the subset contains only two strings.
4) Calculate $\mathrm{NCD}(X)$ as: $\max_{0 \le k \le n-2}\{\mathrm{NCD}_1(Y_k)\}$.

TSDm = NCDm(subset of VAT info)



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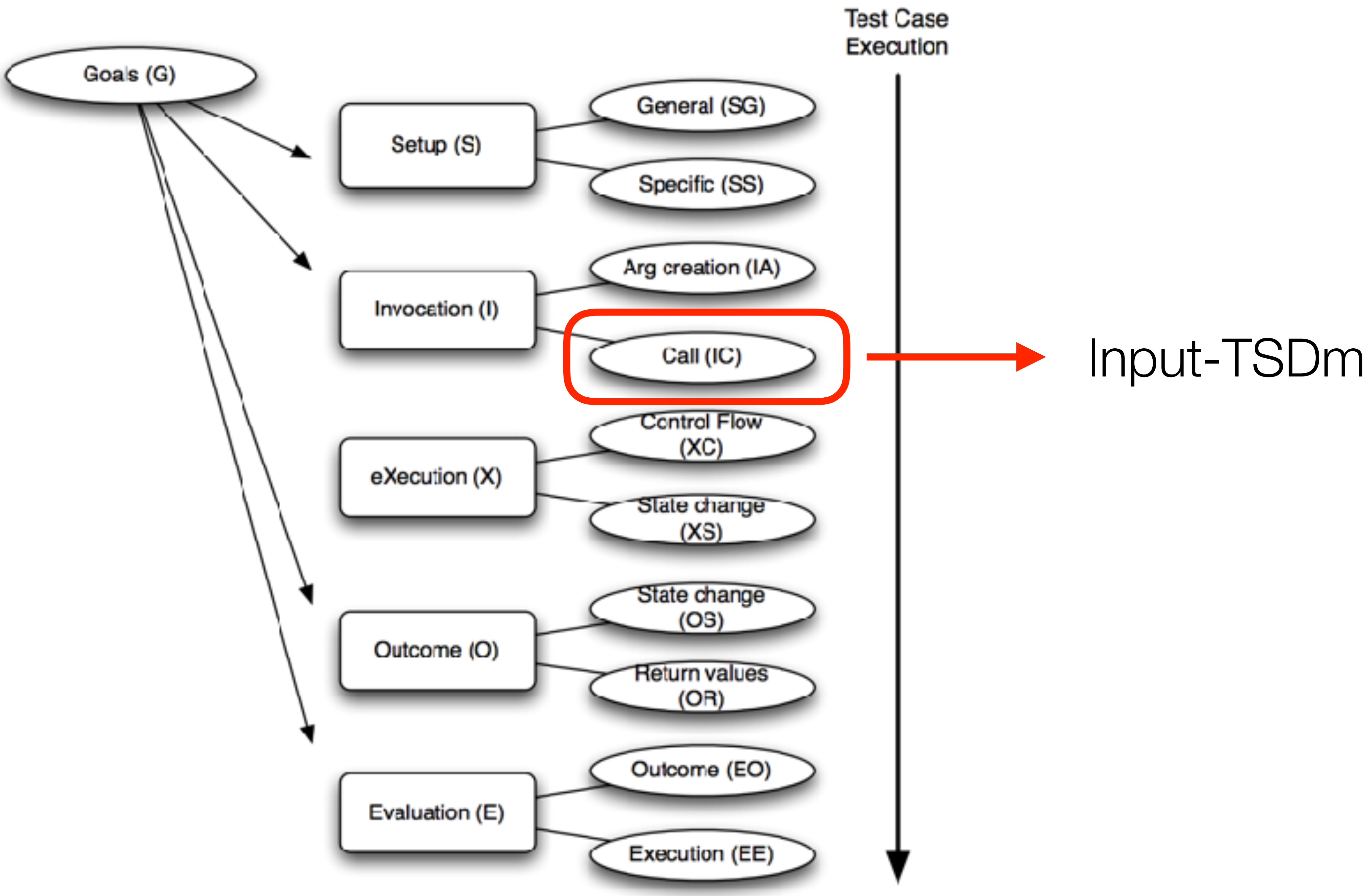

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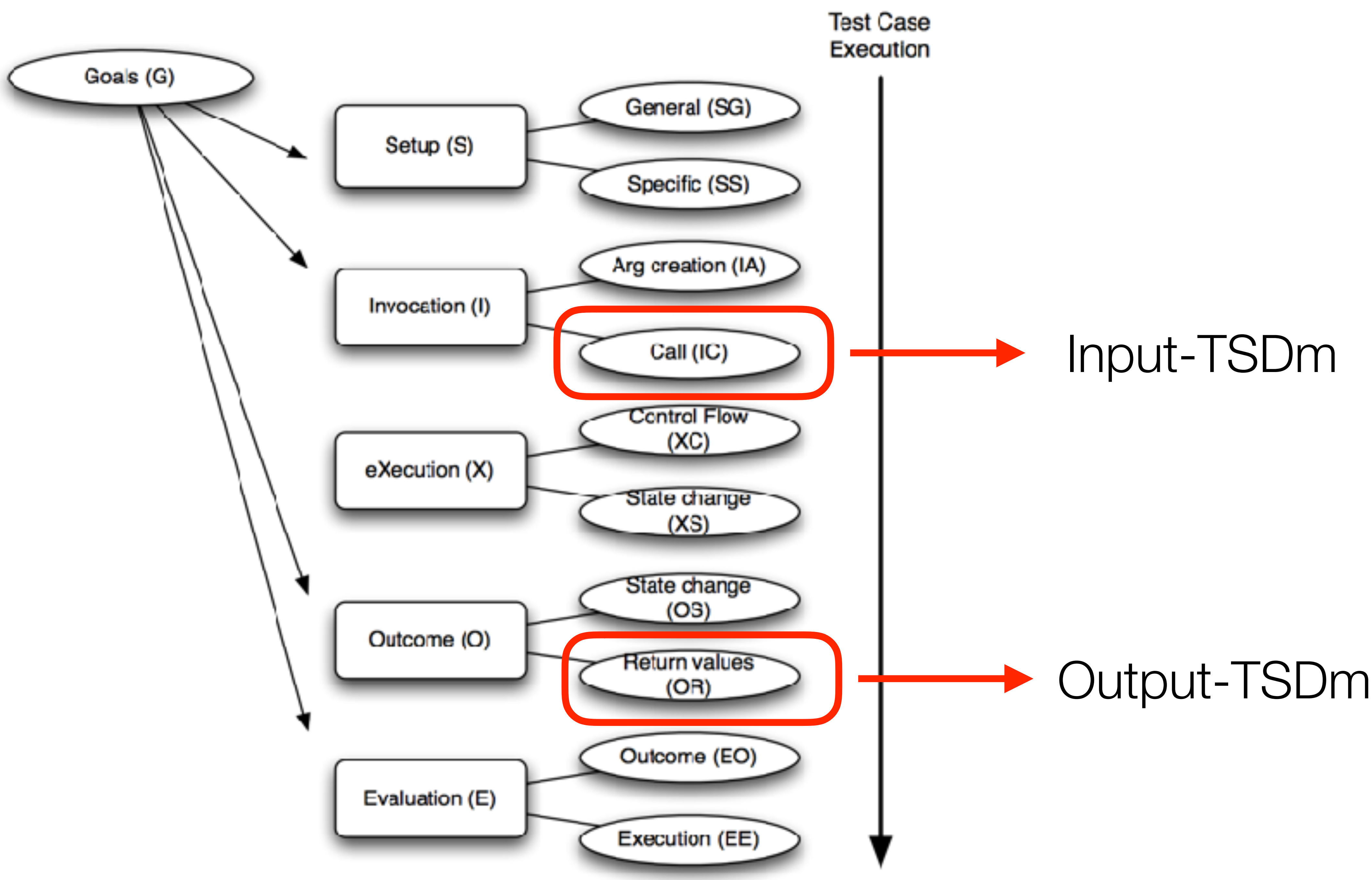

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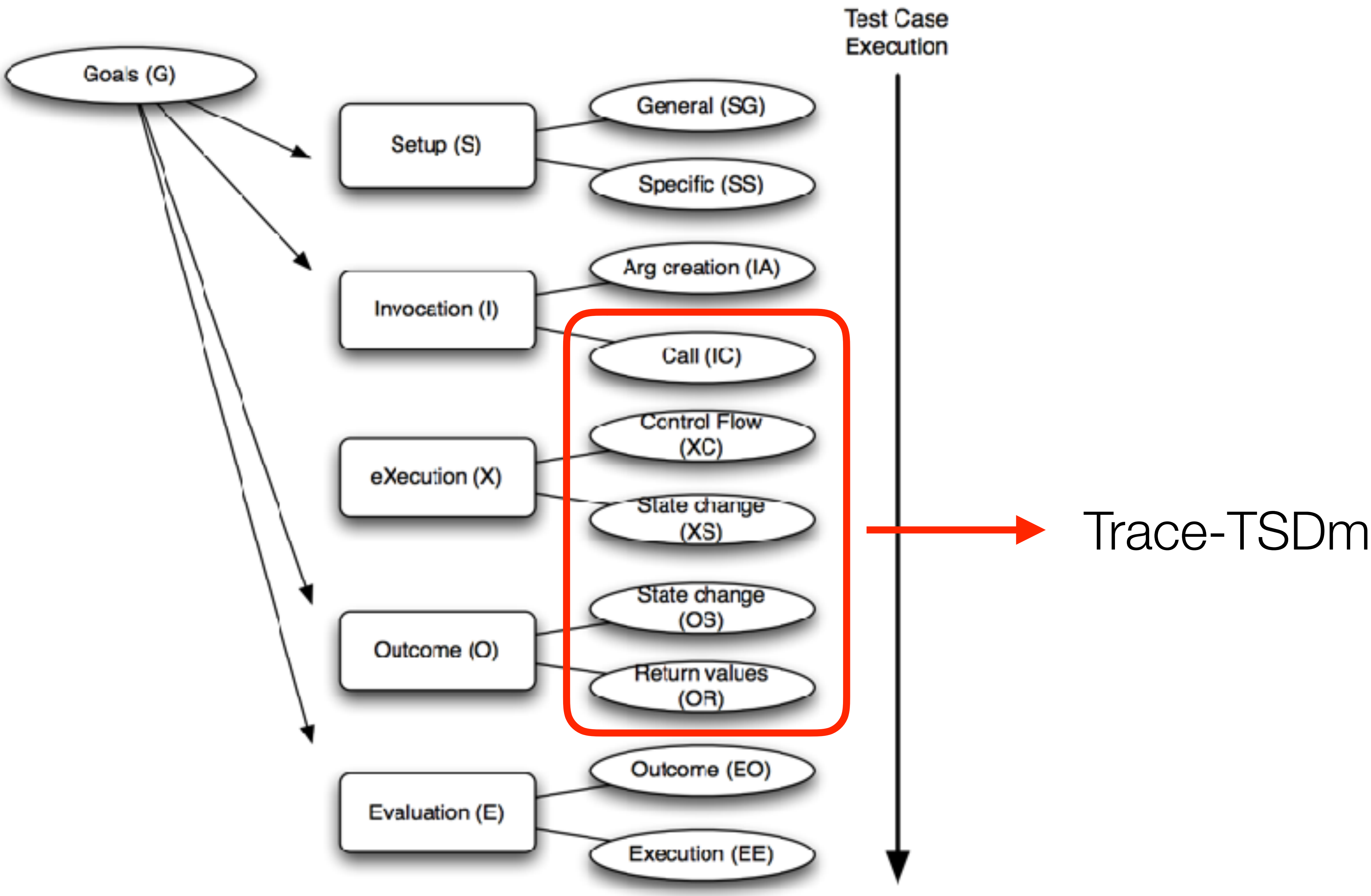

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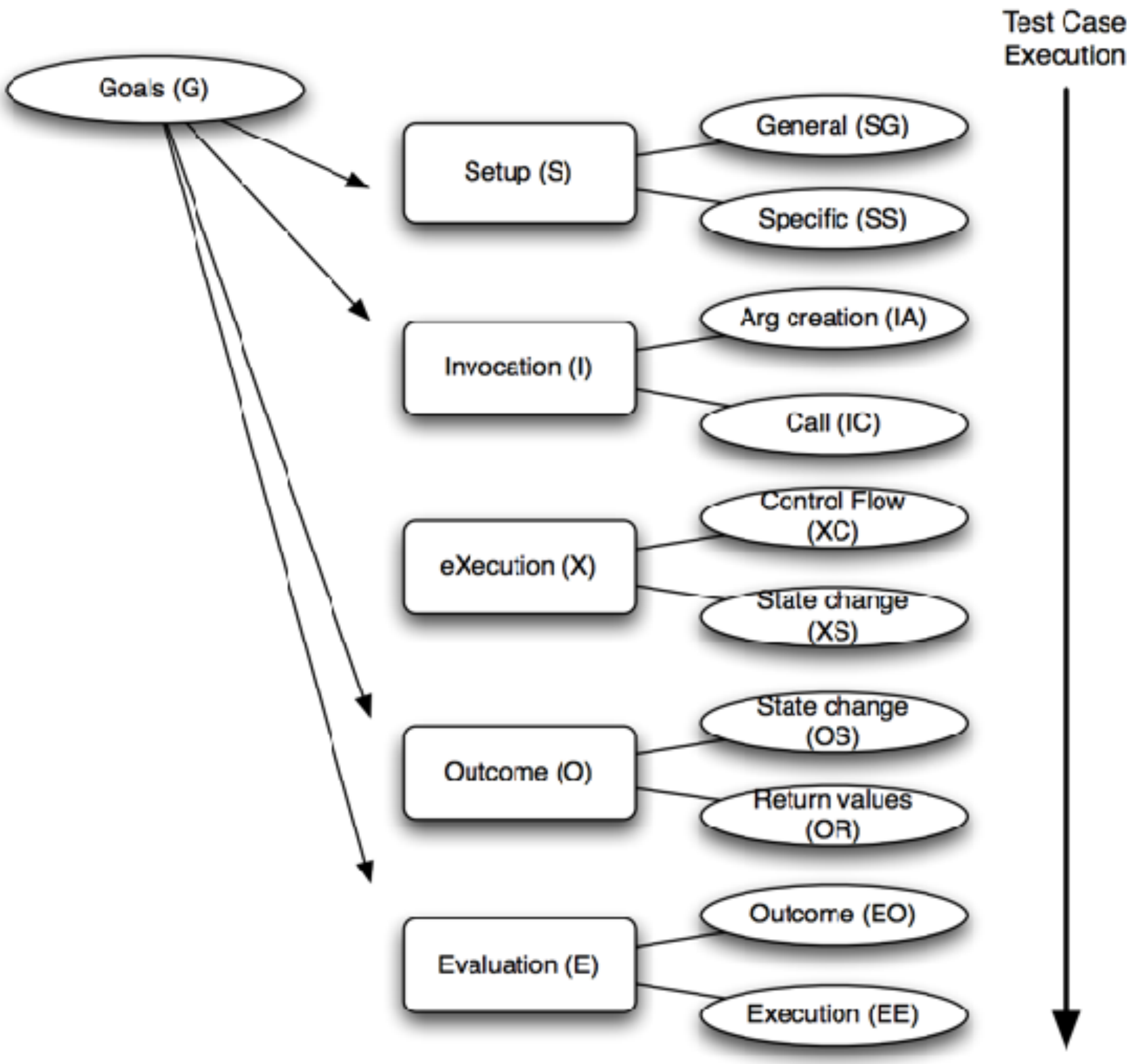

Empirical study here:
Input-TSDm

Empirical study on Input-TSDm

SUT	Input	Size (LOC)	Language	Measure
JEuclid	MathML (XML)	11,556	Java	Instruction Cov
ROME	RSS/Atom (XML)	11,704	Java	Instruction Cov
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Replace	2 strings & 1 Regex	538	C	Fault cov (seeded)

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RQ4 – Fault finding ability: Do test sets selected based on I-TSDm lead to higher fault coverage than test sets based on random selection?

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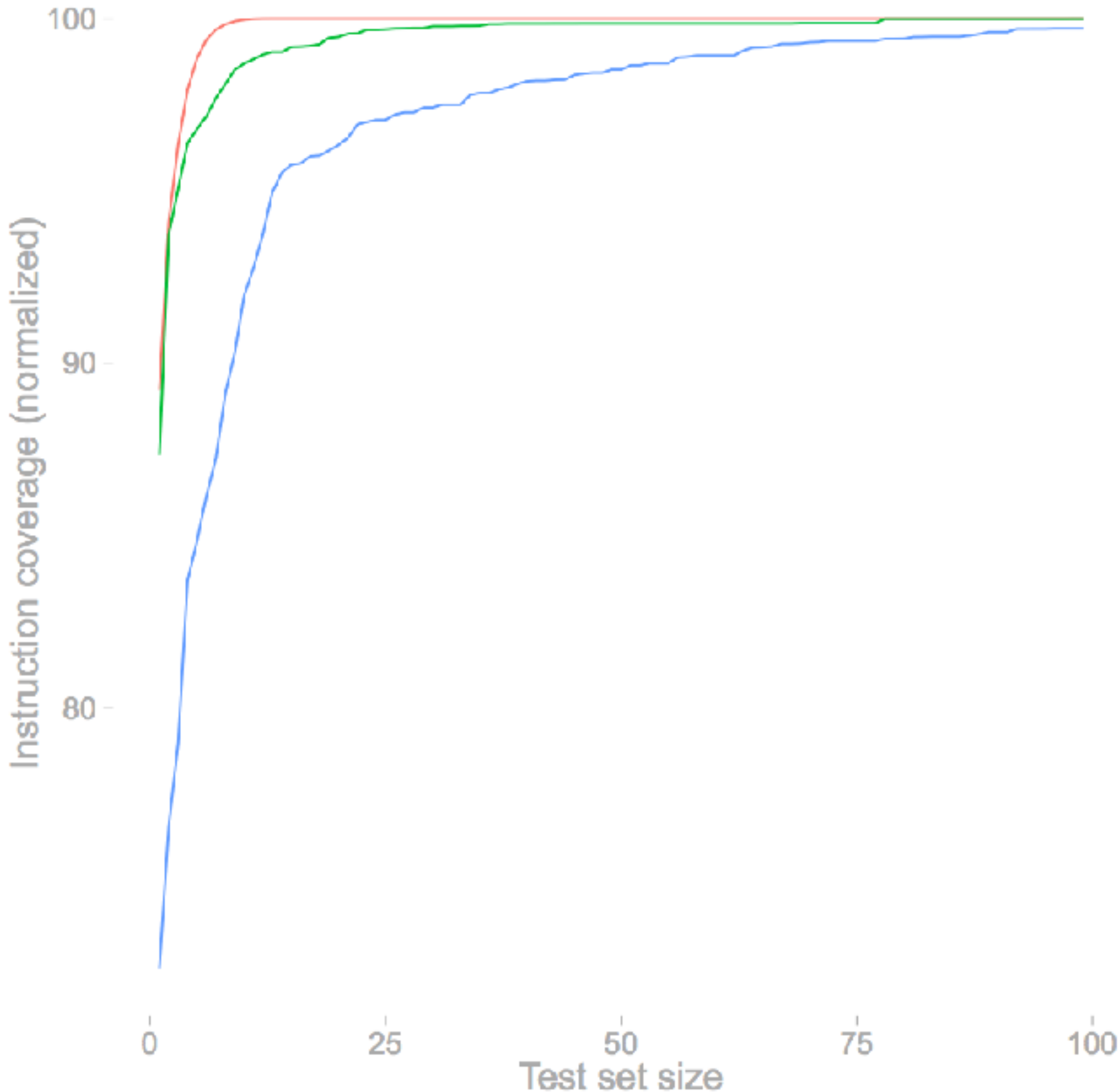

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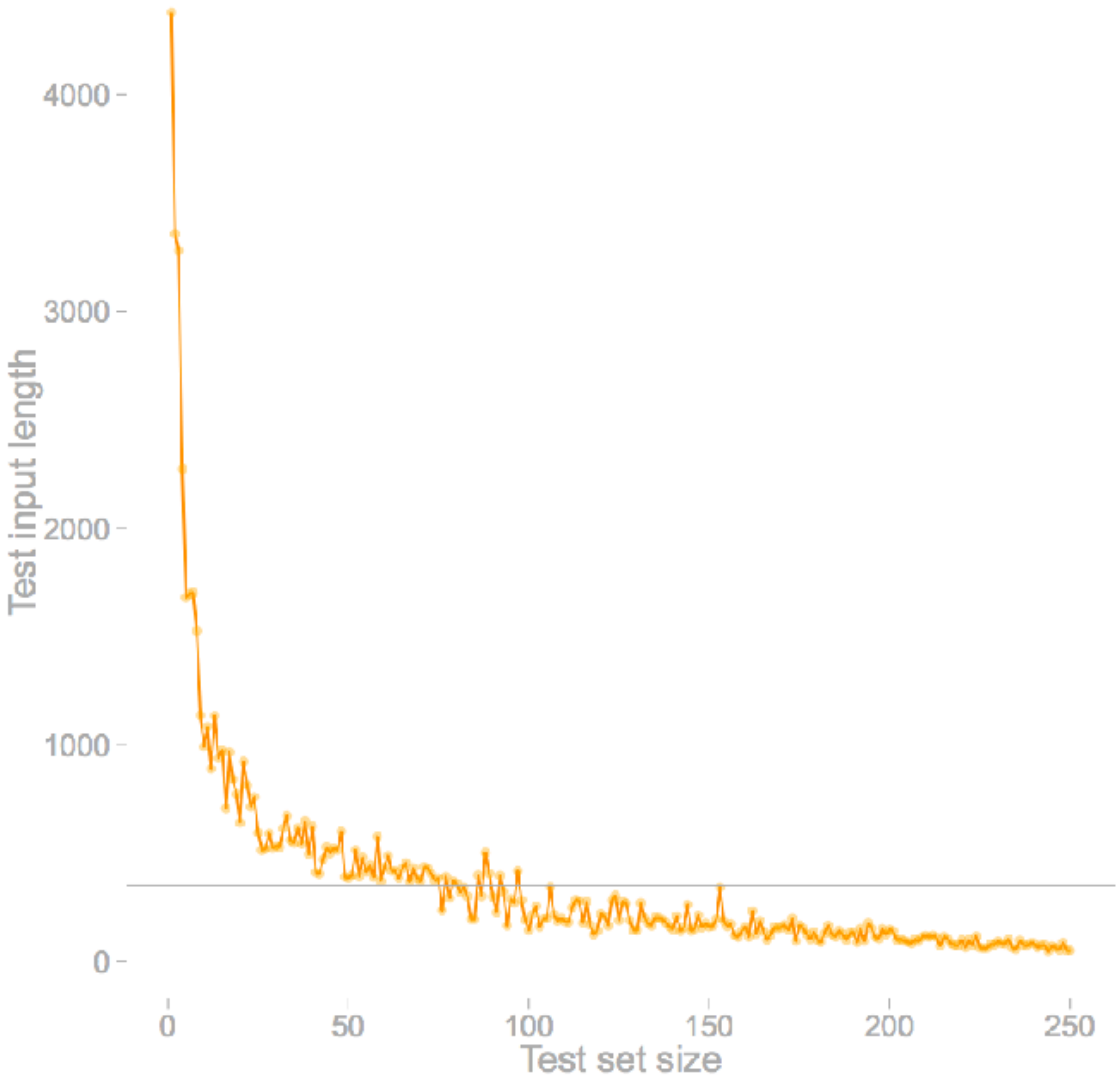

RQ2: Higher code coverage if select based on Input-TSDm?

	Avg. Test Set Size					
	I-TSDm			**Random**		
SUT	**90%**	**95%**	**99%**	**90%**	**95%**	**99%**
JEuclid	29.9	40.9	90.3	82.2	135.3	217.3
NanoXML	1.9	19.4	75.1	18.7	38.2	207.2
ROME	9.1	21.7	51.3	21.9	51.0	129.0

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2.5x

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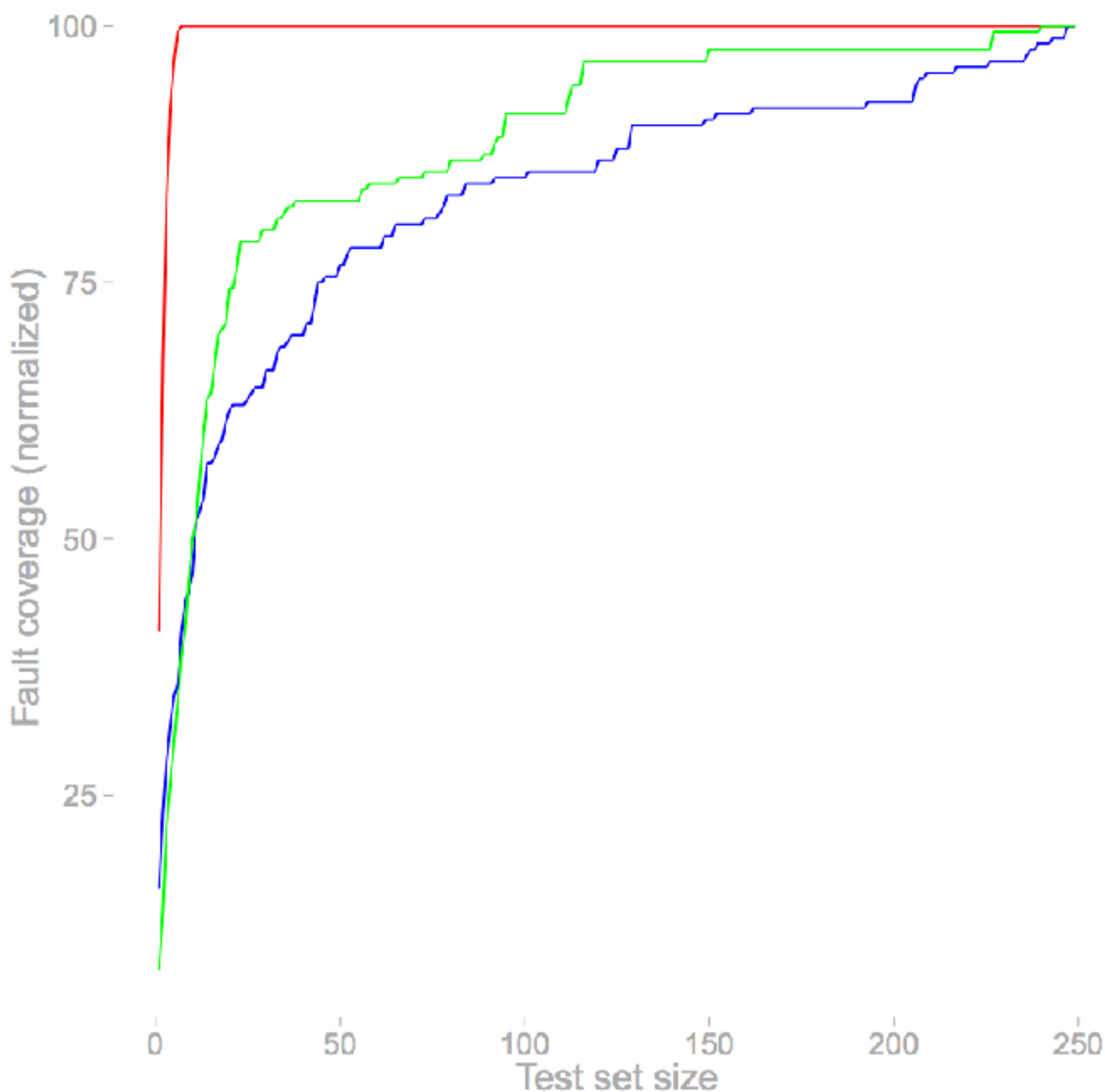

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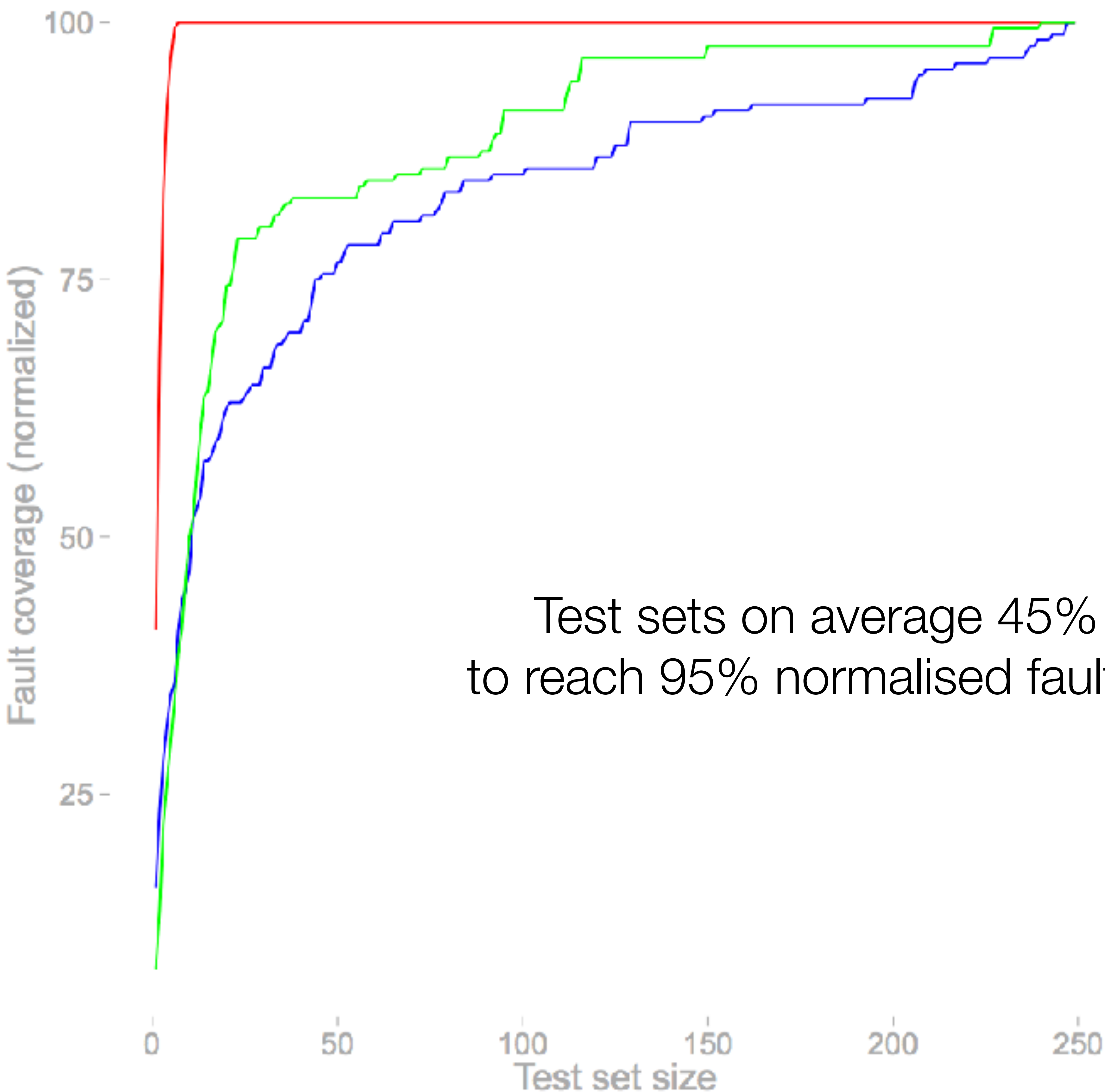

Test sets on average 45% smaller
to reach 95% normalised fault coverage

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  - Also analyse manual test suites & tester behaviour

TSDm is already being applied by others :)

Comparing White-box and Black-box Test Prioritization

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ABSTRACT

Although white-box regression test prioritization has been well-studied, the more recently introduced black-box prioritization approaches have neither been compared against each other nor against more well-established white-box techniques. We present a comprehensive experimental comparison of several test prioritization techniques, including well-established white-box strategies and more recently introduced black-box approaches. We found that Combinatorial Interaction Testing and diversity-based techniques (Input Model Diversity and Input Test Set Diameter) perform best among the black-box approaches. Perhaps surprisingly, we found little difference between black-box and white-box performance (at most 4% fault detection rate difference). We also found the overlap between black- and white-box faults to be high: the first 10% of the prioritized test suites already agree on at least 60% of the faults found. These are positive findings for practicing regression testers who may not have source code available, thereby making white-box techniques inapplicable. We also found evidence that both black-box and white-box prioritization remain robust over multiple system releases.

Although white-box techniques have been extensively studied over two decades of research on regression test optimization [25, 30, 47, 65], black-box approaches have been less well studied [35, 36, 46]. Recent advances in black-box techniques have focused on promoting diversity among the test cases, with results reported for test case generation [9, 16, 18, 50] and for regression test prioritization [14, 35, 56, 69]. However, these approaches have neither been compared against each other, nor against more traditional white-box techniques in a thorough experimental study. Therefore, it is currently unknown how the black-box approaches perform, compared to each other, and also compared to the more traditionally-studied white-box techniques.

Black-box testing has the advantage of not requiring source code, thereby obviating the need for instrumentation and source code availability. Conversely, one might hypothesize that accessing source code information would allow white-box testing to increase source code coverage and, thereby, to increase early fault revelation. It has also been claimed that white-box techniques can be expensive [49] and that the use of coverage information from previous versions might degrade prioritization effectiveness over multiple releases [59]. These hypotheses and claims call out for a thorough com-

NCD in 5 lines of Julia code

```
using Libz
compress(str) = readbytes(ZlibDeflateInputStream(takebuf_array(IOBuffer(str))))
C(str) = length(compress(str))
lexorder(strs) = join(sort(strs), "")
ncd(x, y, c = C) = ( c(lexorder([x, y])) - min(c(x), c(y)) ) / max(c(x), c(y))
```

NCDm would be another ~15 lines to do the looping!

Searching for (Test) Diversity

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BLEKINGE TEKNISKA HÖGSKOLA · BTH ·

DEPARTMENT
OF SOFTWARE
ENGINEERING

Searching for test data with feature diversity

Robert Feldt and Simon Poulding

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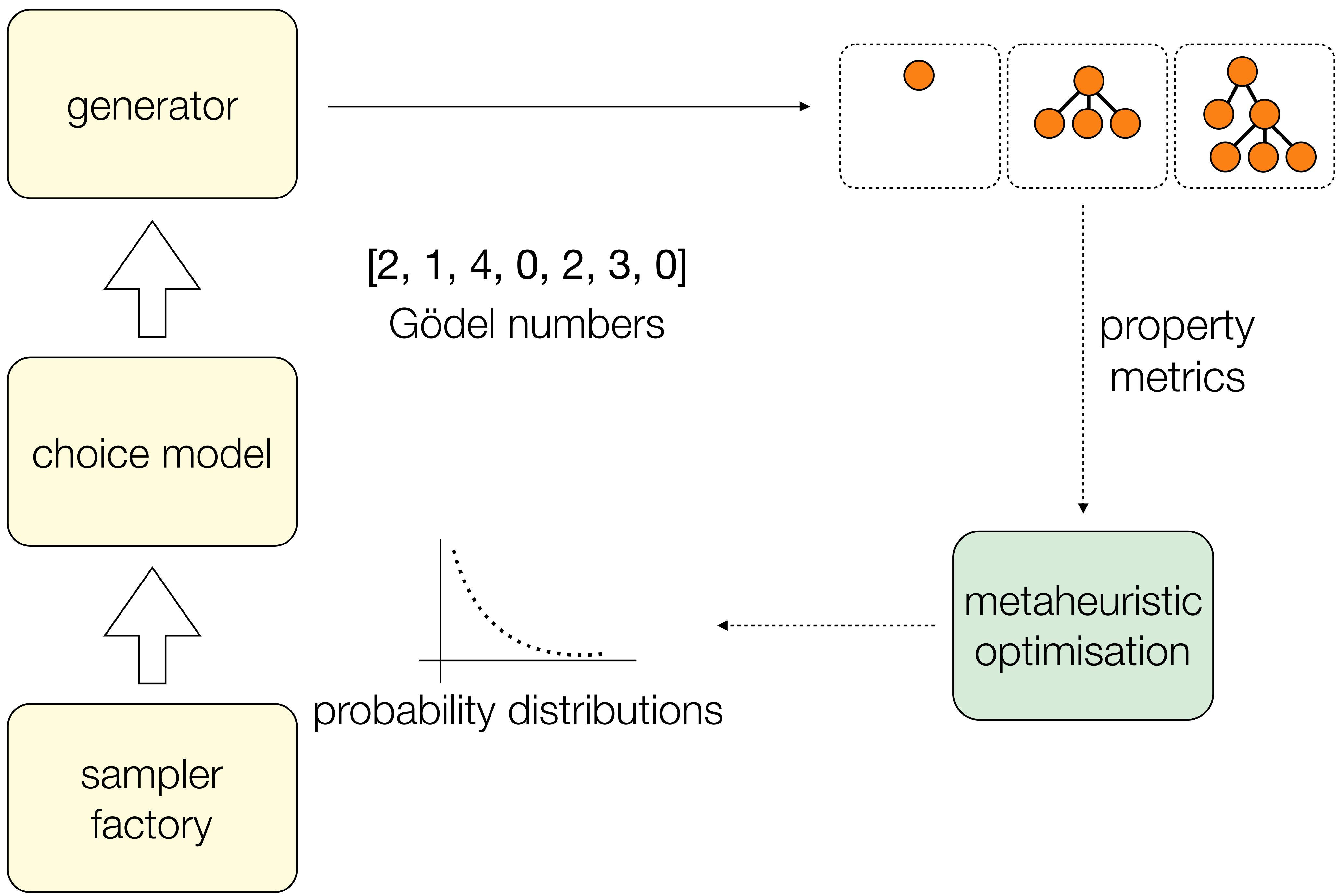
Abstract. There is an implicit assumption in software testing that more diverse and varied test data is needed for effective testing and to achieve different types and levels of coverage. Generic approaches based on information theory to measure and thus, implicitly, to create diverse data have also been proposed. However, if the tester is able to identify features of the test data that are important for the particular domain or context in which the testing is being performed, the use of generic diversity measures such as this may not be sufficient nor efficient for creating test inputs that show diversity in terms of these features. Here we investigate different approaches to find data that are diverse according to a specific set of features, such as length, depth of recursion etc. Even though these features will be less general than measures based on information theory, their use may provide a tester with more direct control over the type of

https://arxiv.org/abs/1709.06017

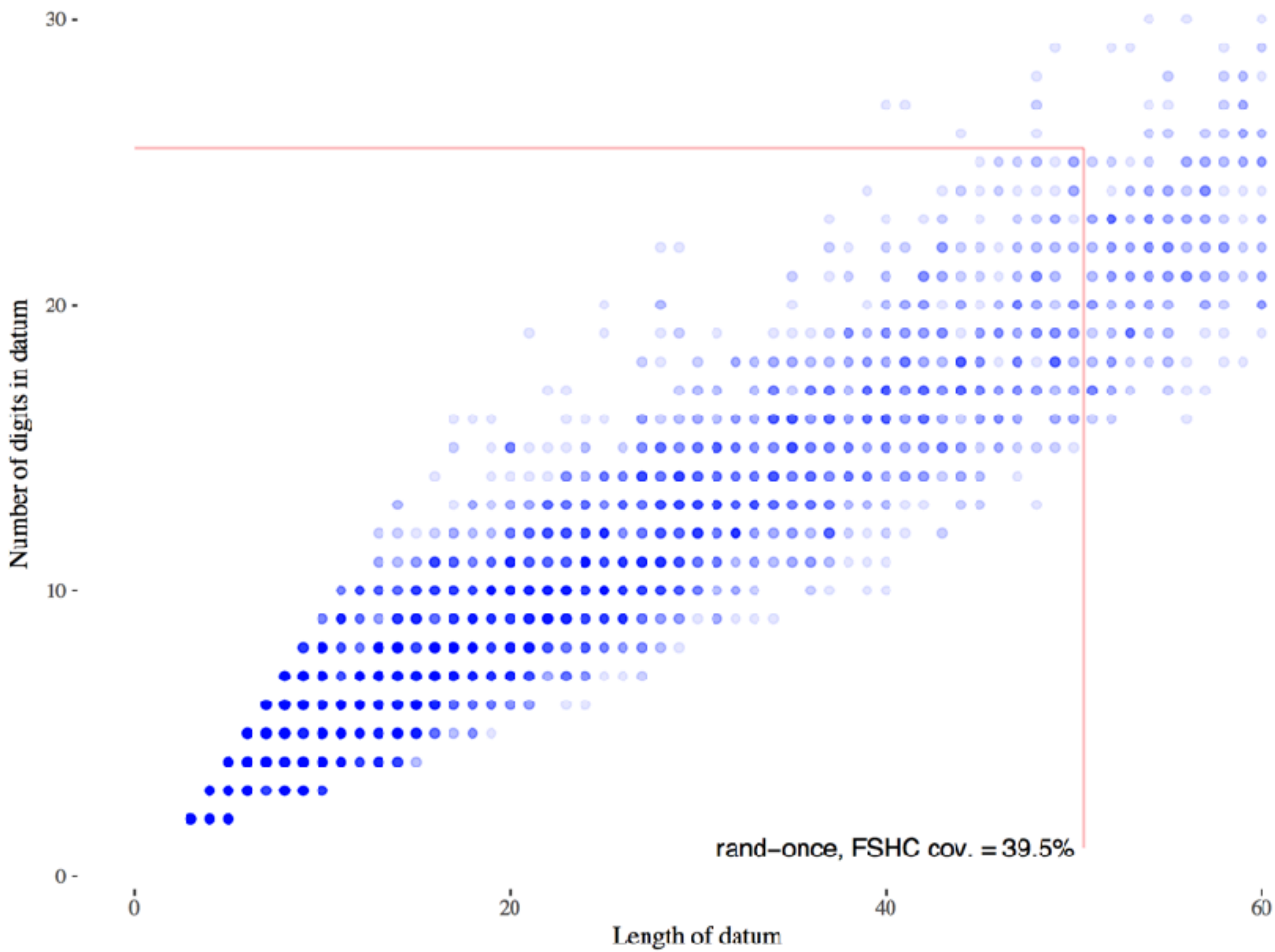
GödelTest Framework

Extracts a model of choice points from a non-deterministic generator; optimises the choice model using metaheuristic optimisation to met bias objectives

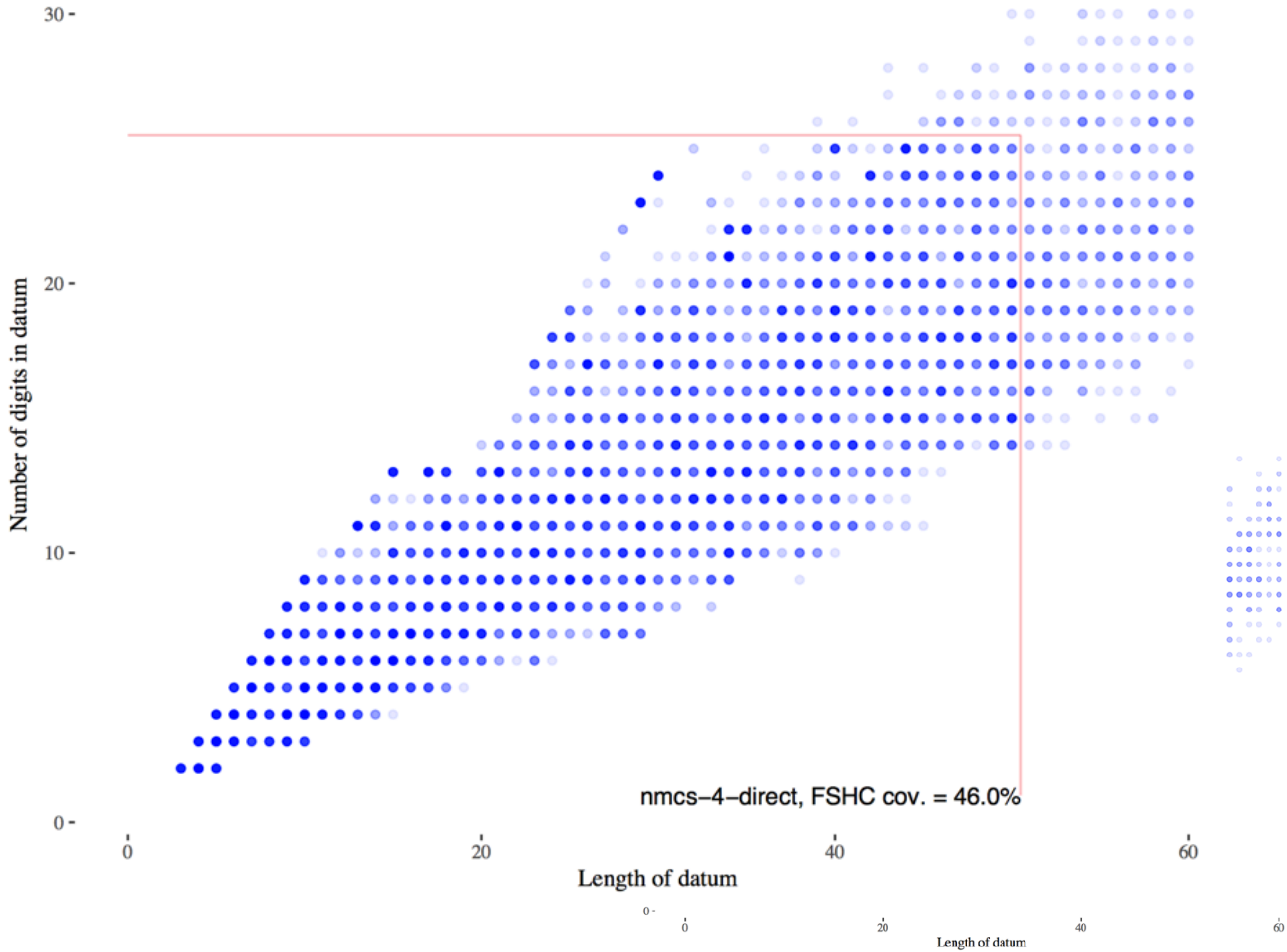


A simple expression generator (for testing calculators)

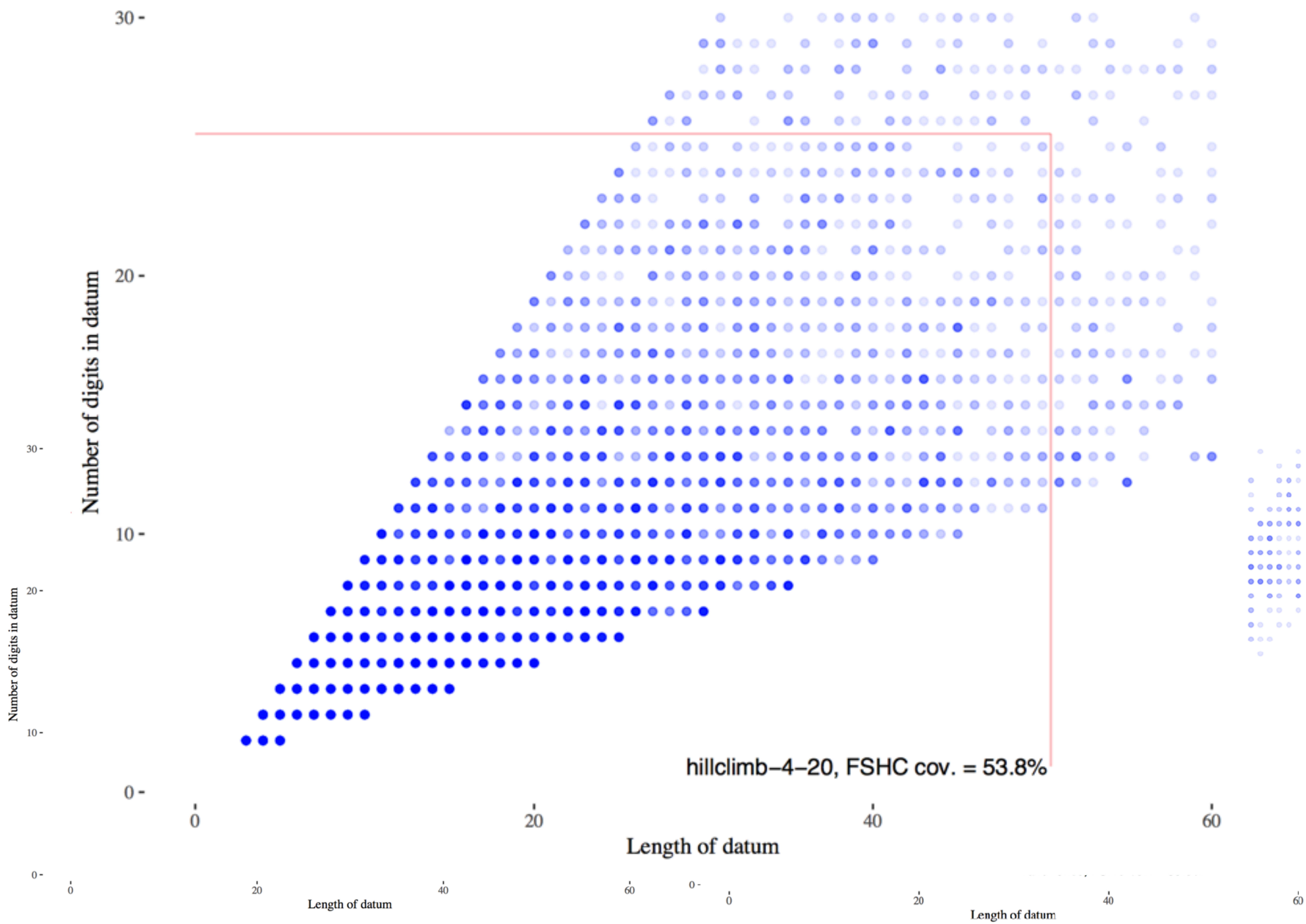
```
@generator ExprGen begin
  start() = expression()
  expression() = operand() *  operator() * operand()
  operand() = "(" * expression() * ")"
  operand() = (choose(Bool) ? "-" : "") * 
join(plus(digit))
  digit() = choose(Int,0,9)
  operator() = "+"
  operator() = "-"
  operator() = "/"
  operator() = "*"
end
```



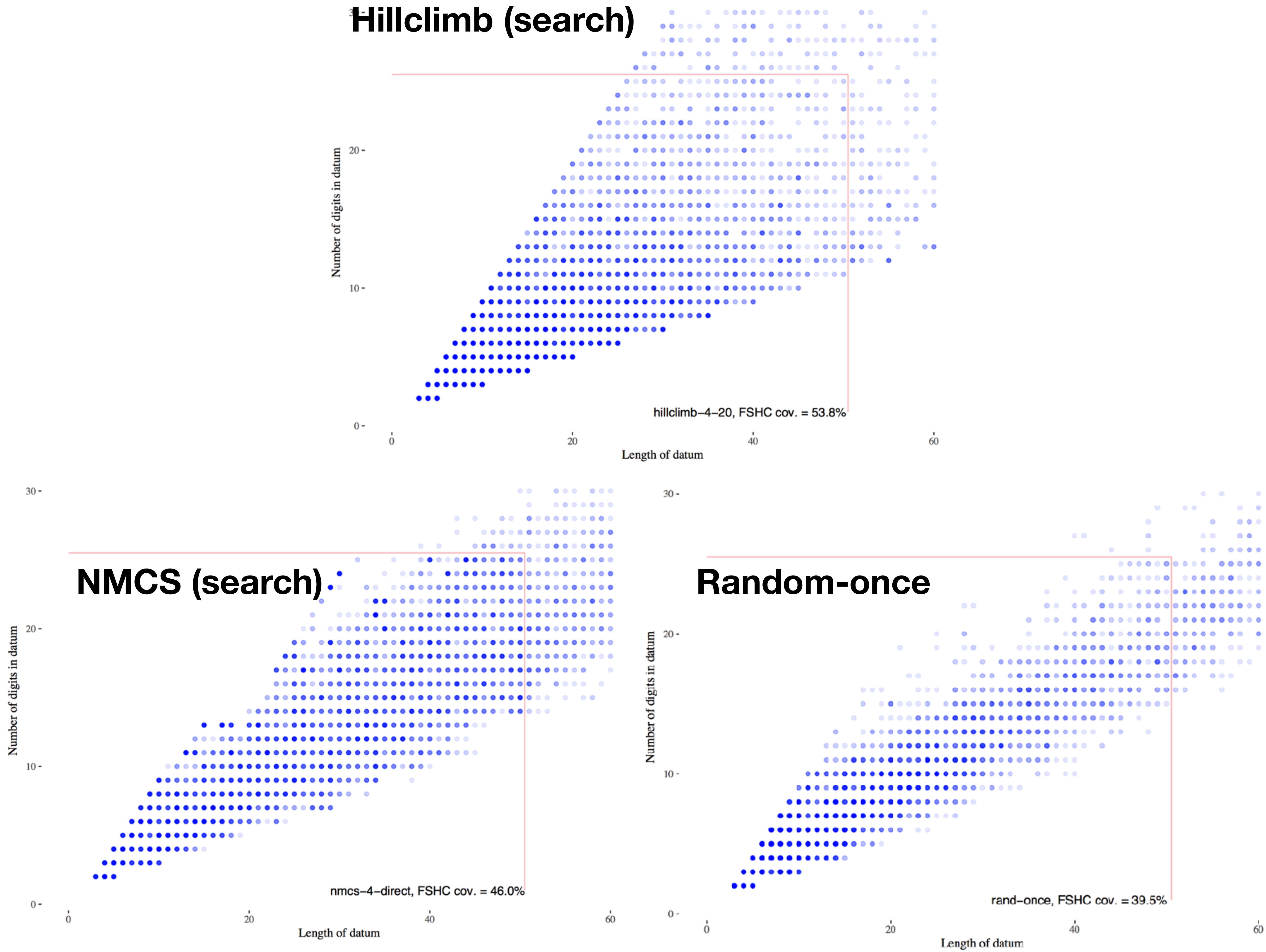
Number of digits in datum
Length of datum
30
20
10
0
0
20
40
60
rand–once, FSHC cov. = 39.5%



30
20
10
0
Number of digits in datum
0
20
40
60
Length of datum
nmcs–4–direct, FSHC cov. = 46.0%



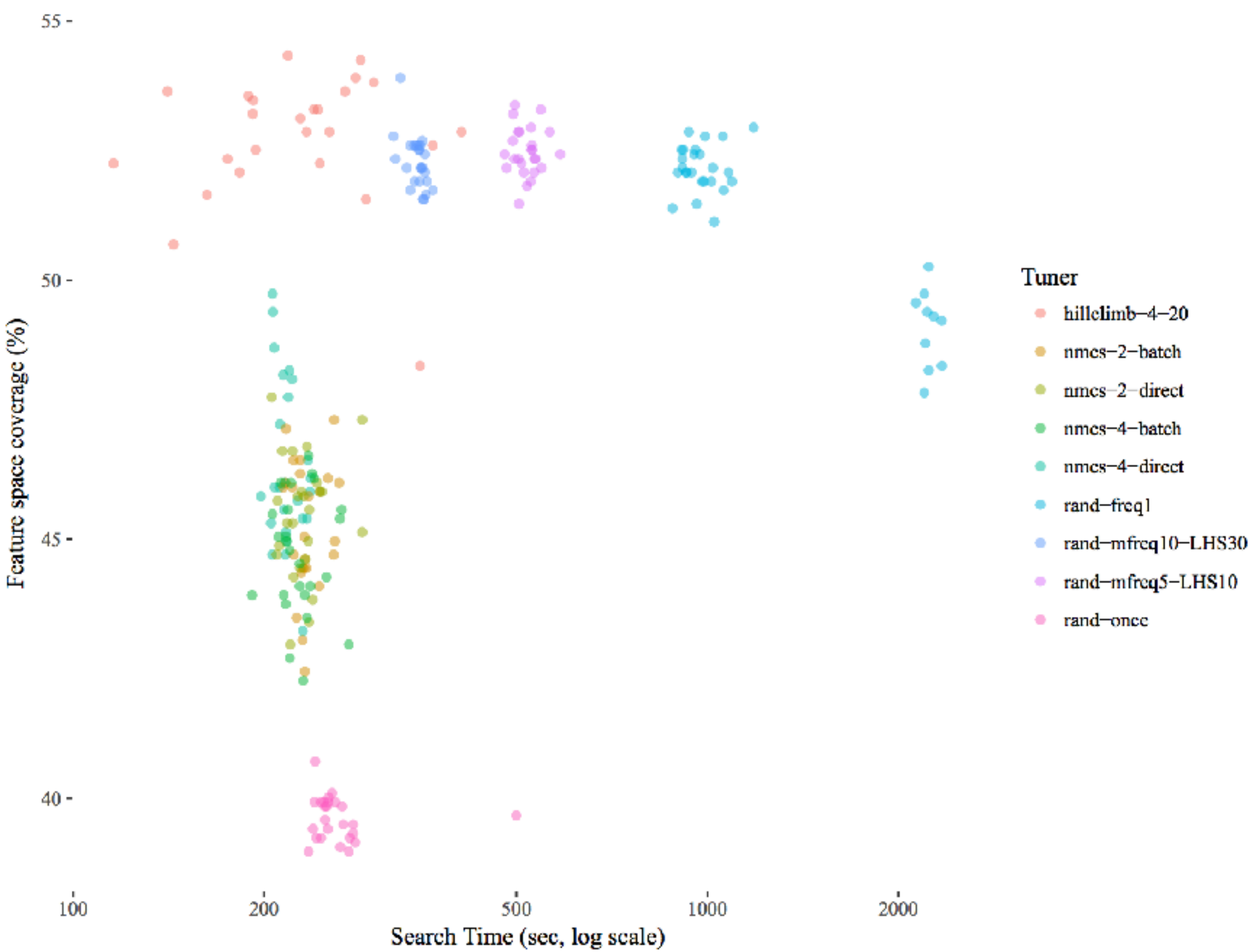
Number of digits in datum
Length of datum
hillclimb−4−20, FSHC cov. = 53.8%



Hillclimb (search)
Number of digits in datum
Length of datum
0
10
20
30
0
20
40
60
hillclimb−4−20, FSHC cov. = 53.8%
NMCS (search)
Number of digits in datum
Length of datum
0
10
20
30
0
20
40
60
nmcs−4−direct, FSHC cov. = 46.0%
Random-once
Number of digits in datum
Length of datum
0
10
20
30
0
20
40
60
rand−once, FSHC cov. = 39.5%

Method	ChoiceModel	Runs	Coverage	std	Time	Preferred
hillclimb − 4 − 20	RecDepth5	25	52.7	1.3	235.9	80.5
rand − mfreq5 − LHS10	RecDepth5	25	52.5	0.5	519.4	65.7
rand − mfreq10 − LHS30	RecDepth5	25	52.3	0.5	348.7	66.8
rand − freq1	RecDepth5	25	52.2	0.5	980.1	61.9
rand − freq1	Default	10	49.1	0.8	2237.1	51.1
nmcs − 4 − direct	Default	25	46.4	1.6	217.6	62.4
nmcs − 2 − direct	Default	25	45.4	1.2	231.3	61.9
nmcs − 2 − batch	Default	25	45.2	1.2	234.3	61.5
nmcs − 4 − batch	Default	25	44.7	1.2	228.6	61.7
rand − once	Default	25	39.6	0.4	265.2	64.0

Table 1. Descriptive statistics on the performance of the 10 investigated methods on the 2-dimensional feature space of string length and number of digits for the ExprGen generator. The 'Runs' columns shows the number of runs per method, 'Coverage' shows the mean FSHC while 'std' is its standard deviation. Finally, 'Time' is the mean search time in seconds and 'Preferred' is the ratio of samples that is within the preference hypercube.


55
50
45
40
Feature space coverage (%)
100
200
500
1000
2000
Search Time (sec, log scale)
Tuner
hillclimb−4−20
nmcs−2−batch
nmcs−2−direct
nmcs−4−batch
nmcs−4−direct
rand−freq1
rand−mfreq10−LHS30
rand−mfreq5−LHS10
rand−once

10th IEEE International Conference on Software Testing, Verification and Validation Workshops

Generating Controllably Invalid and Atypical Inputs for Robustness Testing

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***Abstract*—One form of robustness in a software system is its ability to handle, in an appropriate manner, inputs that are unexpected compared to those it would experience in normal operation. In this paper we investigate a generic approach to generating such unexpected test inputs by extending a framework**

In previous work we have described GödelTest, a framework for generating complex, highly-structured test data [2]. A key feature of GödelTest is a clear separation between *generator* code that defines how to build a test input and a *choice model*

http://ieeexplore.ieee.org/document/7899038/

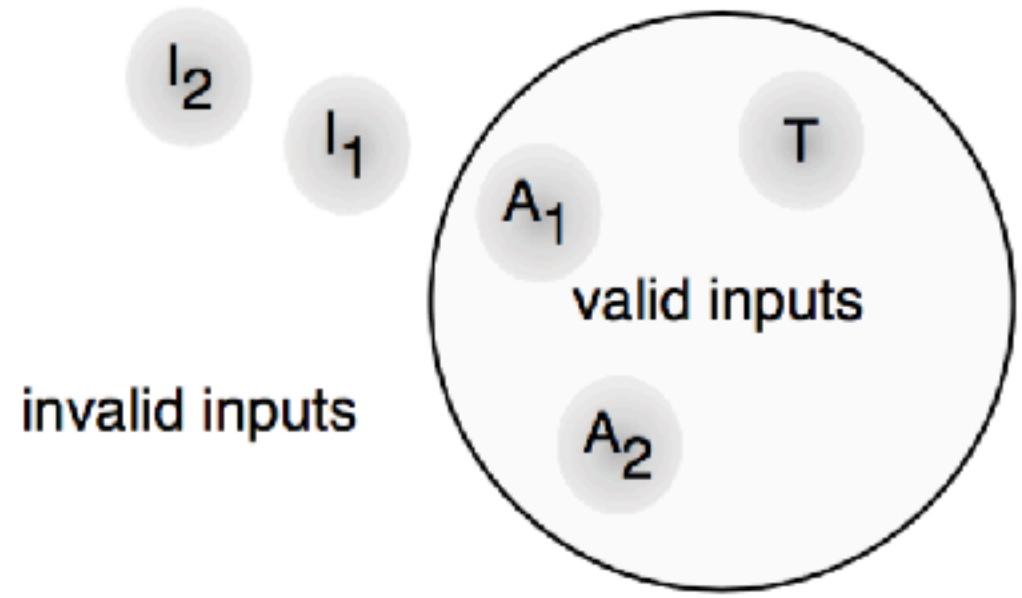

Fig. 2. The intended relationship between the typical (T), atypical (A), and invalid (I) test set categories.

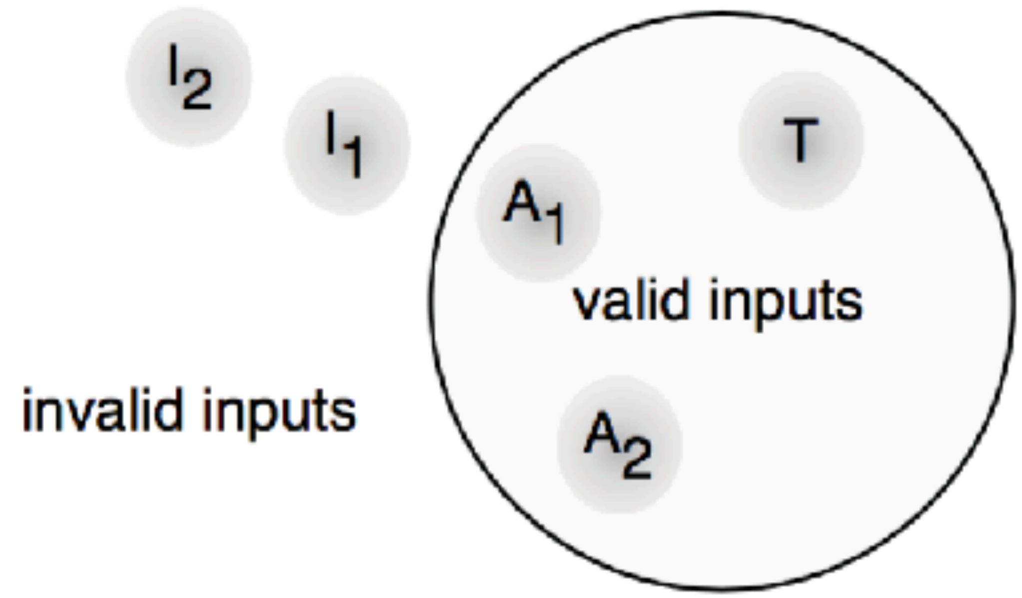

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TABLE I
BYTES OF COMPRESSED WARNING AND ERROR MESSAGES PER CHARACTER OF TEST INPUT FOR THE TEST SET CATEGORIES.

Test Set Category	Compressed Message Bytes per Test Input Character	Hypothesis Test vs.	Hypothesis Test p-value
T	8.59×10^{-4}	—	—
A_1	7.44×10^{-3}	T	$< 10^{-5}$
A_2	9.34×10^{-3}	A_1	1.87×10^{-3}
I_1	1.10×10^{-2}	A_1	$< 10^{-5}$
I_2	1.23×10^{-2}	I_1	3.83×10^{-3}

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  - (soon in report) Boundary Value testing.
- Focusing on available information also has added value in industry collaborations.

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