Théo Matricon

2025–current

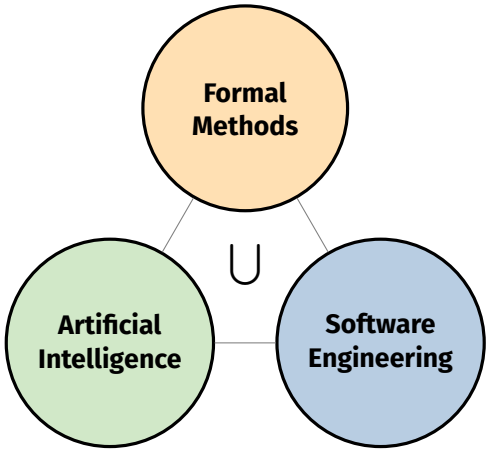
Postdoc with Mathieu Acher
Code Generation, Reproducibility
DiverSE, Software Engineering team
IRISA, Rennes

2021–2024

PhD supervised by Nathanaël Fijalkow
Scaling domain agnostic techniques for program synthesis
M2F, Formal Methods team
LaBRI, Bordeaux

Medical Condition (RQTH)

Research Contributions

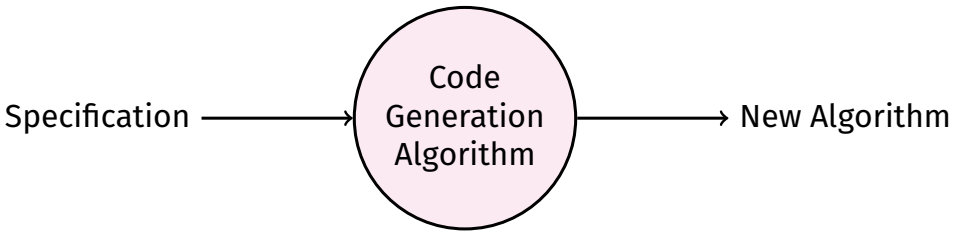


Selected Publications

- 2026, 2 TOSEM ($Q1$) accepts with major revisions
- 2026, MSR (A)
- 2025, TACAS (A)
- 2025, AAAI (top 20%) (A^*)
- 2025, IST ($Q1$)

  Postdoc
- 2022, AAAI (top 20%) (A^*)

PhD Motivation



PhD Motivation: In Practice

Specifications

Logic

$$\forall a, b$$
$$f(a, b) \geq a$$
$$f(a, b) \geq b$$
$$f(a, b) \in \{a, b\}$$

Examples

$$f(1, 5) = 5$$
$$f(2, 1) = 2$$
$$f(-3, -9) = -3$$

Natural Language

'Write a function that takes the maximum of its two arguments.'

Produced Algorithm

```
def max(a: int, b: int) ->int:
    if a <=b:
        return b
    else:
        return a
```

Program Synthesis: Problem

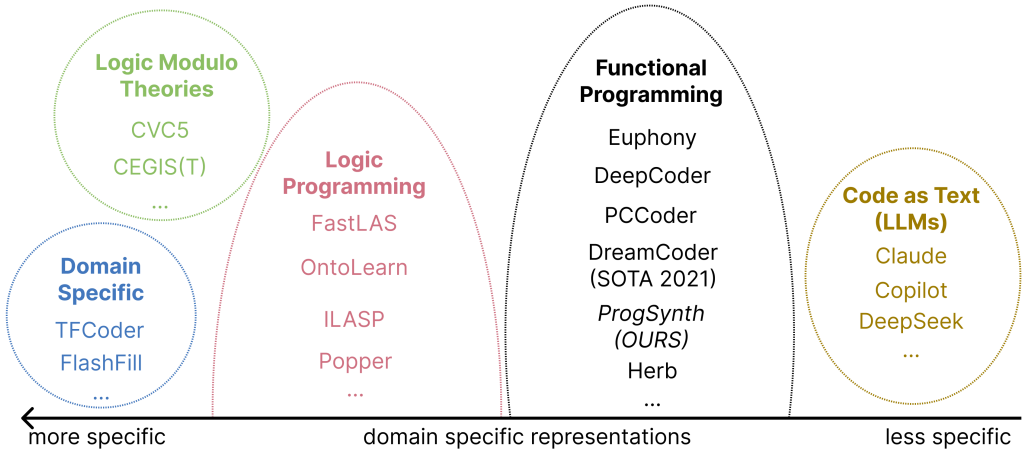
Input

- the search space G:
  a deterministic tree grammar
- a specification $\mathcal{C}$:
  checks if a program $p \in \mathcal{L}(G)$ matches the specification

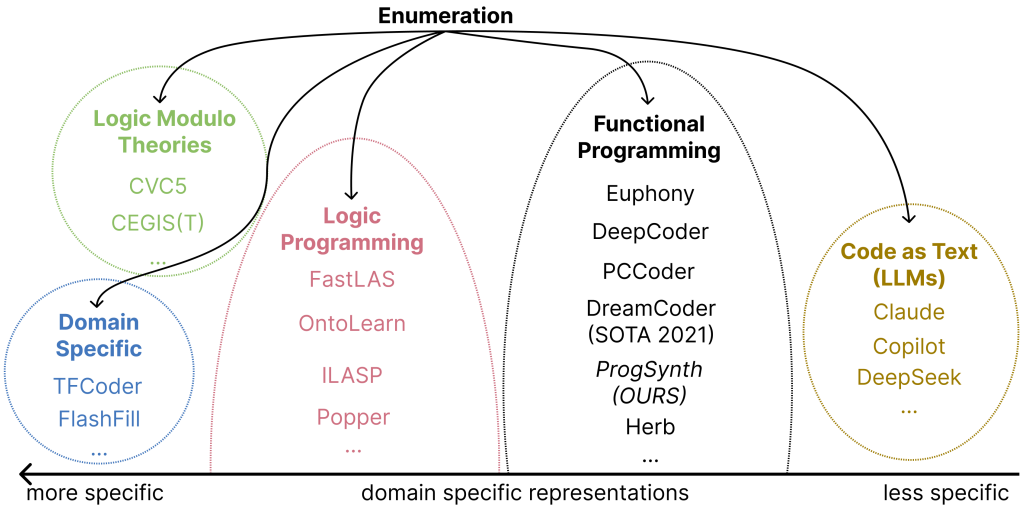
Output

- a program in the search space that matches the specification:
  $p \in \mathcal{L}(G)$ such that $\mathcal{C}(p) = \checkmark$

Program Synthesis: Frameworks



Program Synthesis: Frameworks



Program Synthesis: Enumeration Problem

Input

- the search space G:
  a deterministic tree grammar with a cost for each tree
- a specification $\mathcal{C}$:
  checks if a program $p \in \mathcal{L}(G)$ matches the specification

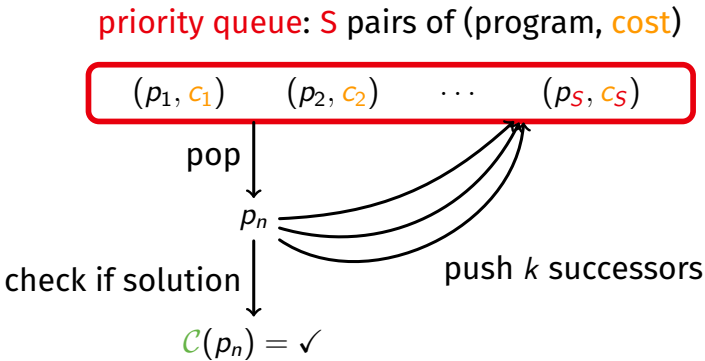
Goal

- enumeration of programs in order of non-decreasing costs

Delay

- time complexity between enumeration of two successive programs
  in terms of number of enumerated programs

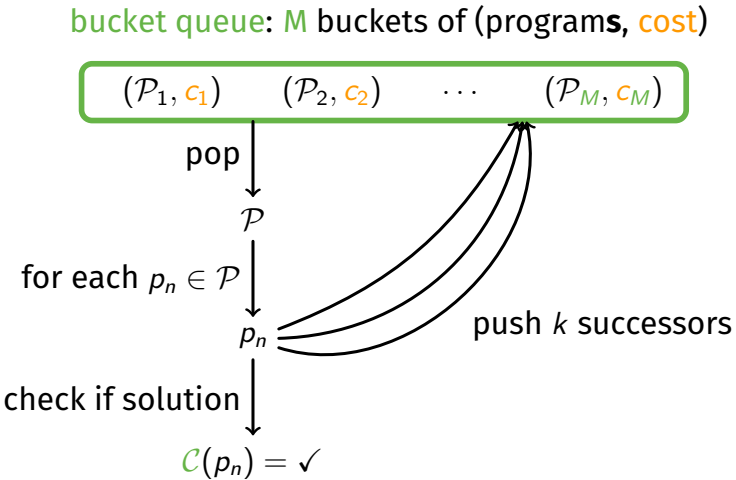
Enumeration Algorithm Before Our Contribution



At step n

$S = O(n)$
$k = O(1)$

Our Contribution: Constant Delay



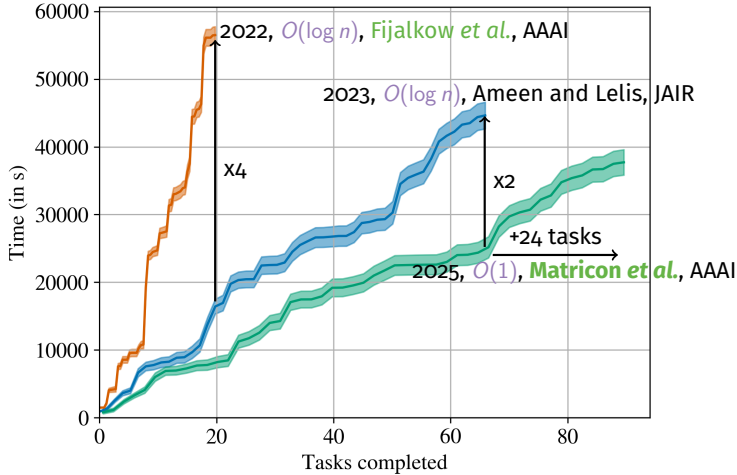
At step n

$M = O(1)$
$k = O(1)$

Our Contribution: Empirical Results

Major Papers

- 2017, ML + Enum., Balog *et al.*, ICLR
- 2018, $O(\log n)$, Lee *et al.*, PLDI



Our Contribution: Summary

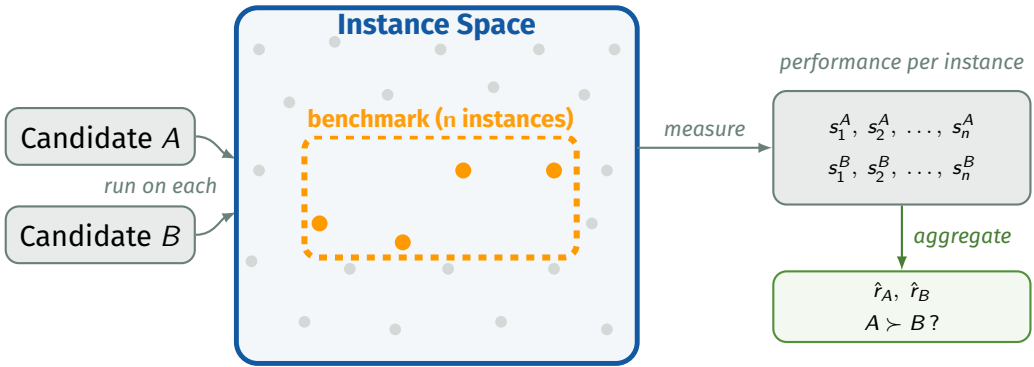
We prove bounded differences in cost:
$\exists M,\ \forall n,\ cost\_next(p_n) - cost(p_n) \leq M$

This implies: priority queues $O(\log n)$ $\rightarrow$ bucket queues $O(1)$

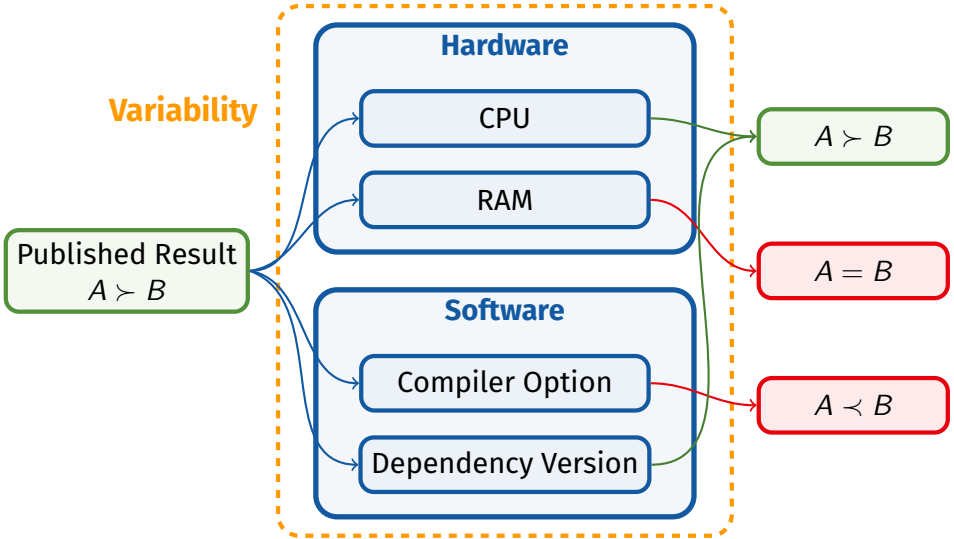
Impact

Published in **AAAI 2025** (+oral: 20% of accepted papers).
Fastest ranked enumeration for program synthesis **in practice**.
First algorithm with $O(1)$ delay $\rightarrow$ closes open question.

Evaluations



Evaluations: In Practice



My Research Project

Observations

- Exponential growth in scientific publications **[1]**
- Reproducibility crisis in computational science
- Evaluations are a key aspect of reproducibility

[1] Bornmann and Mutz, "Growth rates of modern science: A bibliometric analysis based on the number of publications and cited references", JAIST

My Research Project

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How to design reliable and efficient evaluations?

Reliable $\rightarrow$ formal guarantees

Efficient $\rightarrow$ reduce cost of evaluations

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Main Challenges

SE Modelling the huge hardware and software variability

AI Predicting heterogeneous evaluation data

FM Giving formal guarantees while still being efficient

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My Research Project

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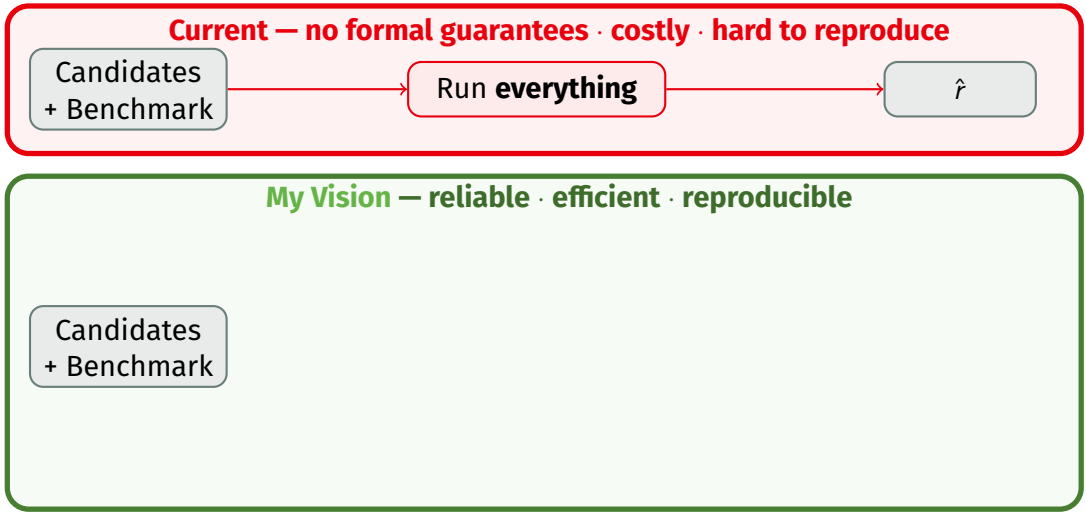

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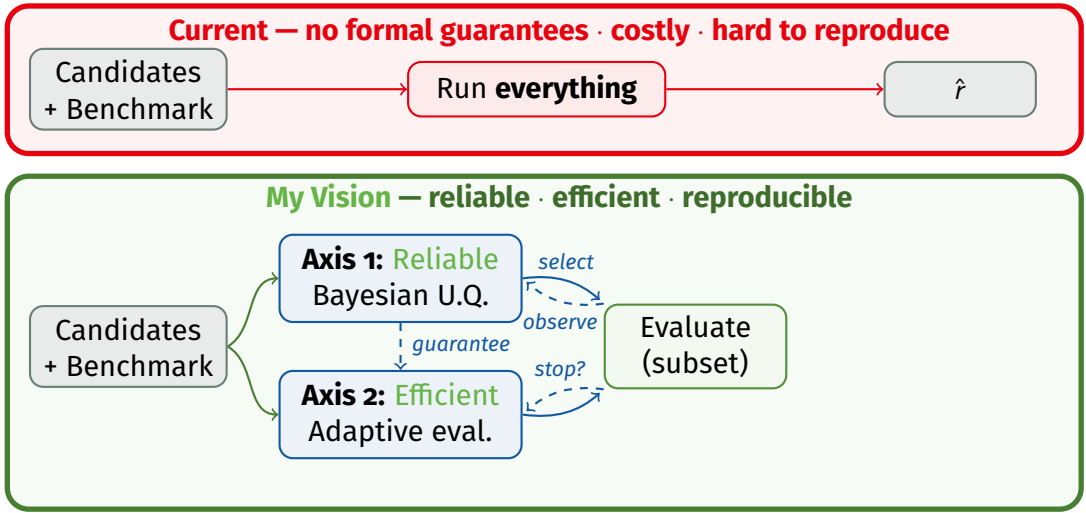

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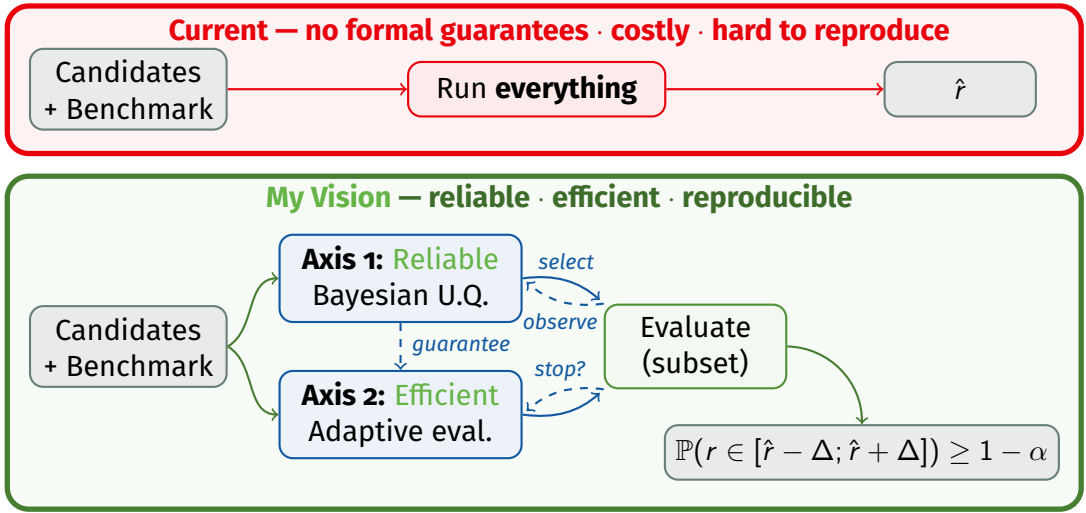

Classic Approach vs. Our Approach

Classic Approach

What is evaluated

Run all n instances — exhaustively

Our Approach

What is evaluated

Adaptive subset + early stopping
(∼50% fewer runs **[1]**)

[1] Matricon *et al.*, "Efficiently ranking software variants with tiny benchmarks" under revision at TOSEM

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assumes i.i.d. & normality

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Adjustable complexity

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Single environment assumed
results may not transfer

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Multi-environment hierarchical model
quantifies generalizability

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Classic Approach vs. Our Approach

Classic Approach

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Run all n instances — exhaustively

Statistical framework

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Variability

Single environment assumed
results may not transfer

Reproducibility

binary: reproduced or not

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Adaptive subset + early stopping
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Statistical framework

Adjustable complexity

Variability

Multi-environment hierarchical model
quantifies generalizability

Reproducibility

graded: exact → ordinal → trend

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Axis 1: Reliable Evaluations

Variability

CPU-A • GCC-12 • Linux

$\hat{r}_A = 0.82 \quad \hat{r}_B = 0.75 \quad A \succ B$

CPU-B • GCC-14 • Linux

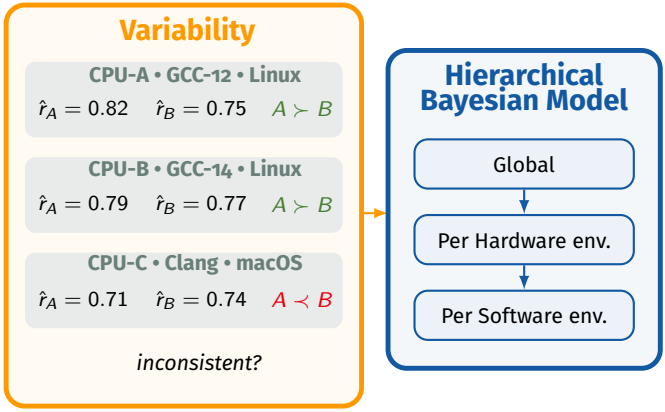
$\hat{r}_A = 0.79 \quad \hat{r}_B = 0.77 \quad A \succ B$

CPU-C • Clang • macOS

$\hat{r}_A = 0.71 \quad \hat{r}_B = 0.74 \quad A \prec B$

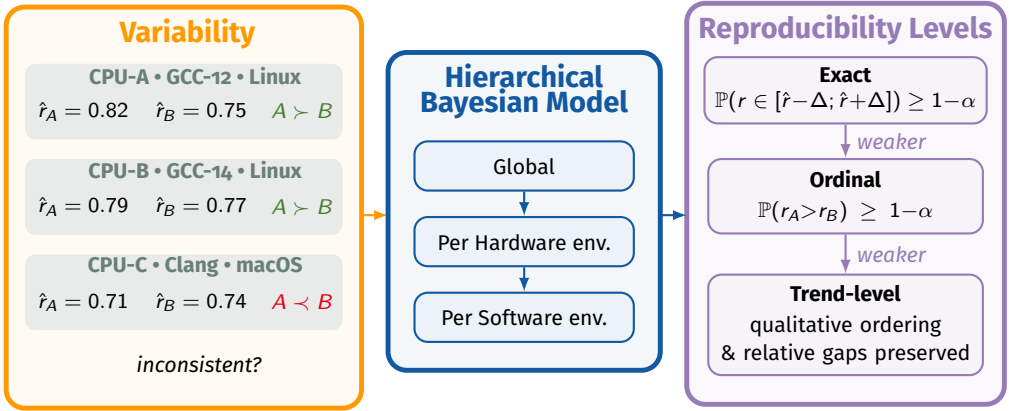
inconsistent?

Axis 1: Reliable Evaluations



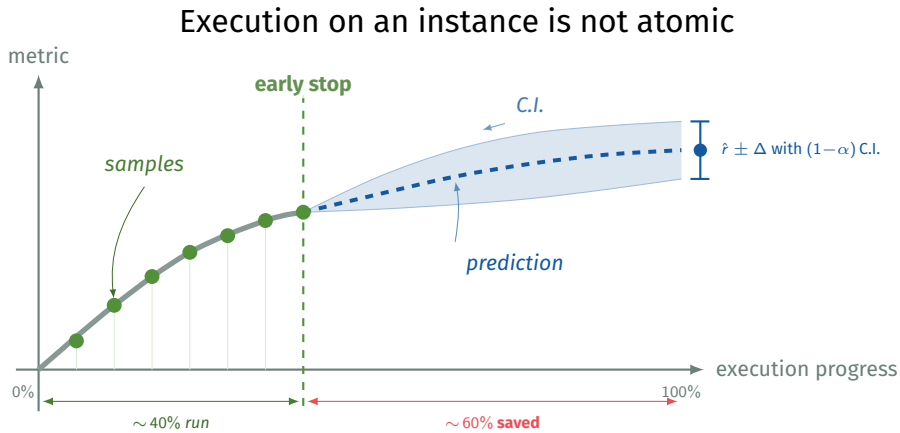
Ernst, "Bayesian hierarchical modelling for tailoring metric thresholds", MSR, 2018

Axis 1: Reliable Evaluations



Ernst, "Bayesian hierarchical modelling for tailoring metric thresholds", MSR, 2018

Axis 2: Efficient Evaluations



Integration

Transversal project with many applications in empirical fields

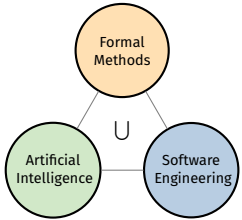
→ CRIStAL, UMR 9189, Lille, **Spirals** (SEEDS)

Frugality and Evaluations: Clément Quinton, Romain Rouvoy
Trust: Pierre Bourhis (Citadelle)
Statistics: Scool team

→ IRISA, UMR 6074, Rennes, **DiverSE** (rRaise)

Reproducibility: Mathieu Acher, Olivier Barais, Djamel E. Khelladi
Frugality: *Romain Lefeuvre*, Quentin Perez

Théo Matricon

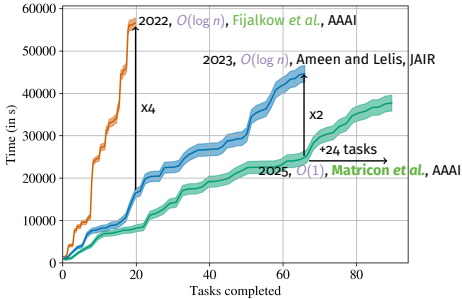


Selected Publications

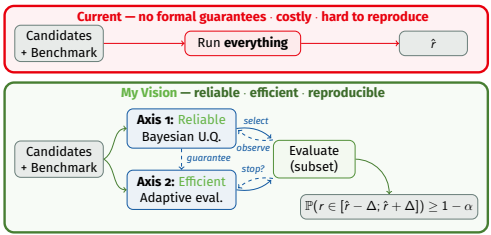
2 AAAI →

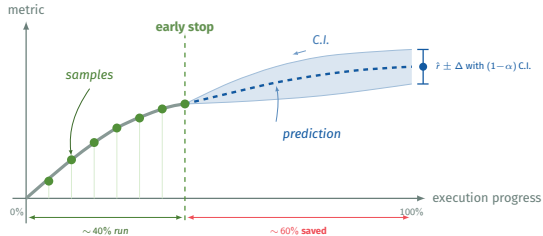
IST, MSR, 2 TOSEM

TACAS



Research Project





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