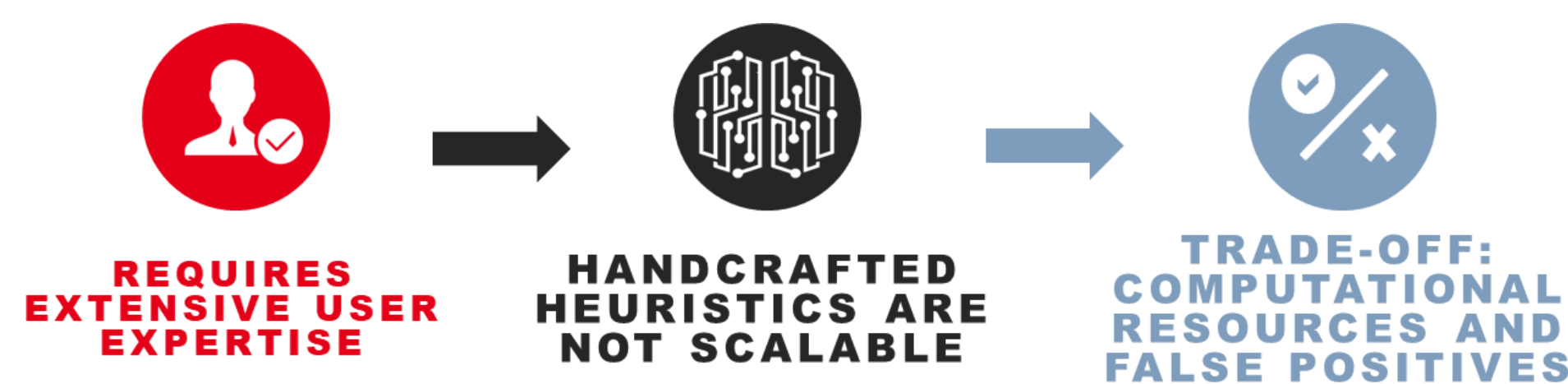




## Context

- Abstract Interpretation** is crucial for software verification and bug detection, but false alarms limit practical adoption
- State-of-the-art analyzers (e.g. Frama-C/Eva, Mopsa, Astrée, etc...) employ **precision-enhancing** strategies such as loop unrolling
- These strategies are computationally **expensive** and require **manual parameterization**, which is challenging even for domain experts
- Prior approaches:
  - Per-program** configuration via iterative tuning (time-consuming)
  - ML-based** heuristics relying on handcrafted features (poor generalization)
- Research Gap:** Need for **automated, general, feature-free** strategy parameterization



## Motivating Example

1. #include <stdio.h>

2. int fib(int n) {

3. int a = 1, b = 1;

4. // @ loop unroll 100;

5. for (int i = 3; i <= n; i++) {

6. int tmp = a;

7. a += b;

8. b = tmp;

9. }

10. return a;

11. }

12. void main() {

13. // @ loop unroll 0;

14. for (int i = 1, n; i <= 10; i++) {

15. printf("Enter a number <= 30: ");

16. scanf("%d", &n);

17. if (n > 0 && n <= 30) {

18. printf("fib(%d)=%d\n", n, fib(n));

19. break;

20. }

21. }

22. }



**Frama-C/Eva is not requested to unroll the loop:**

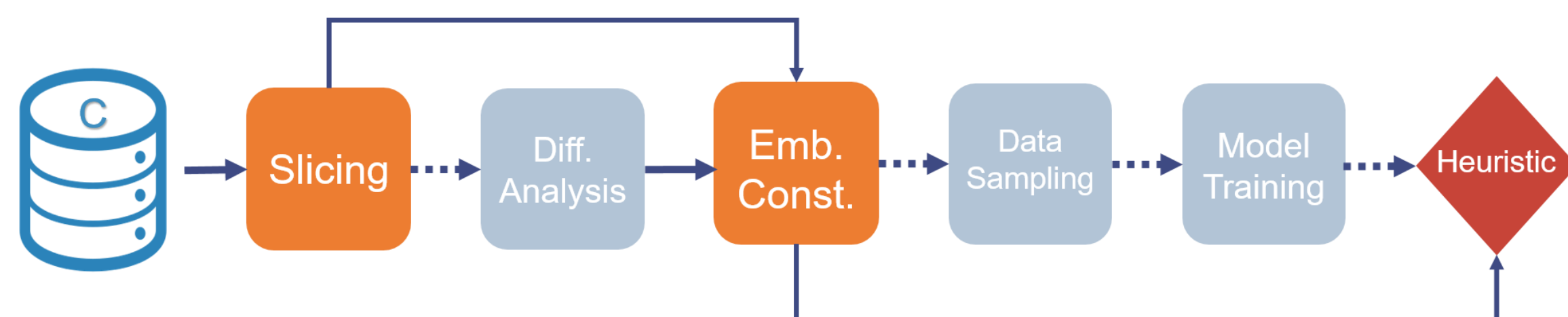
- a** and **b** are in  $[1, 2^{31} - 1]$
- Overflow alarm upon **a += b**



**Frama-C/Eva is requested to unroll the loop:**

- Per-iteration** analysis of loop at line 4
- Precise approximation of **a** and **b** ranges
- The false alarm disappears

## The Loupe Framework



- Large-scale, **self-contained** C files
- Extracts** loops with dependencies; focuses on loop behavior
- Uses analyzer as **oracle**; labels loops by **comparing** with/without unrolling
- CPG** for graph models or **IR2Vec/Sparrow** for vector approaches
- Benchmarks** XGBoost, SOTA, CodeLLMs, and GNNs

## Efficacy

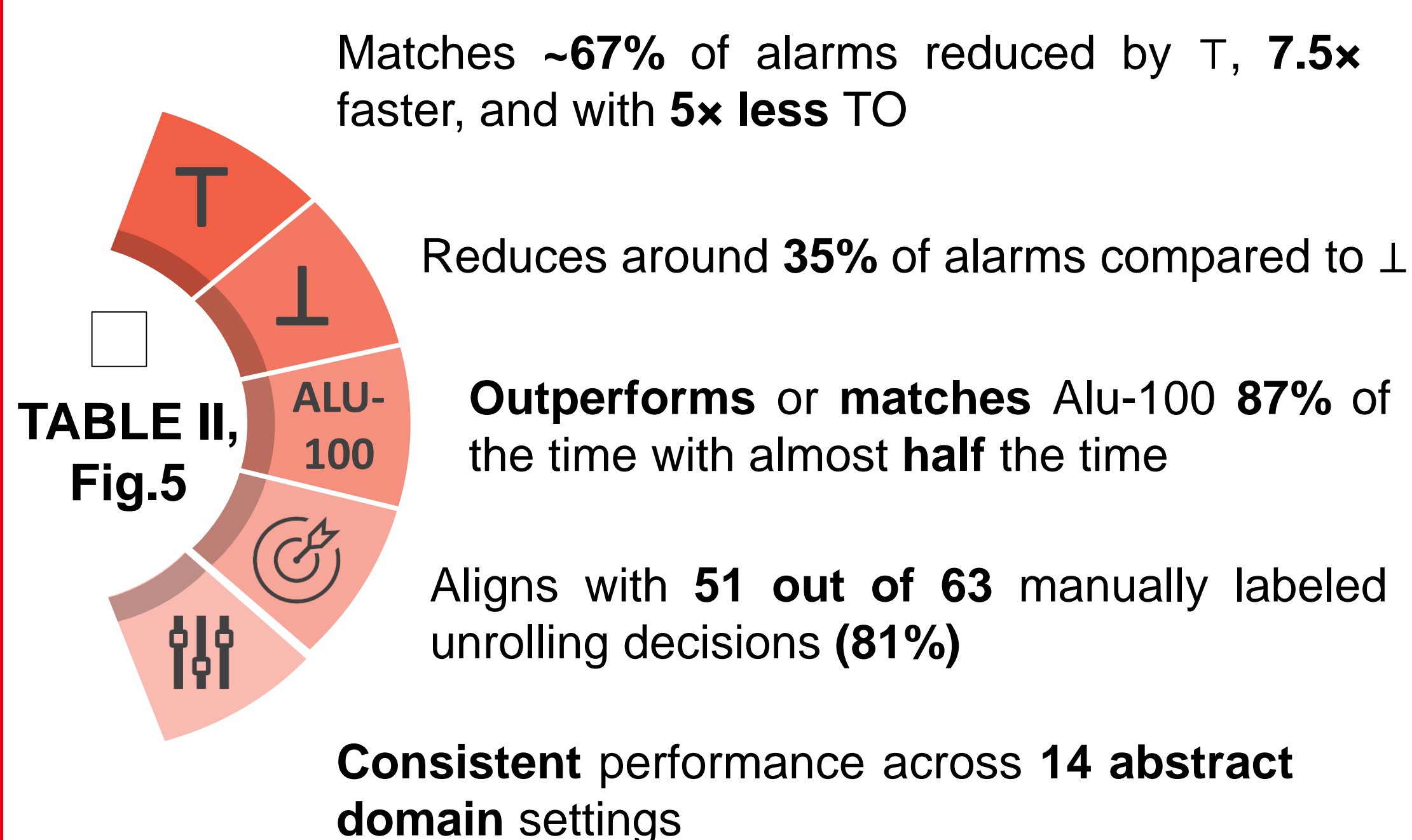
### RQ1:

☐ Loop unrolling heuristic learning comparison on preprocessed and real-world datasets. TABLE I

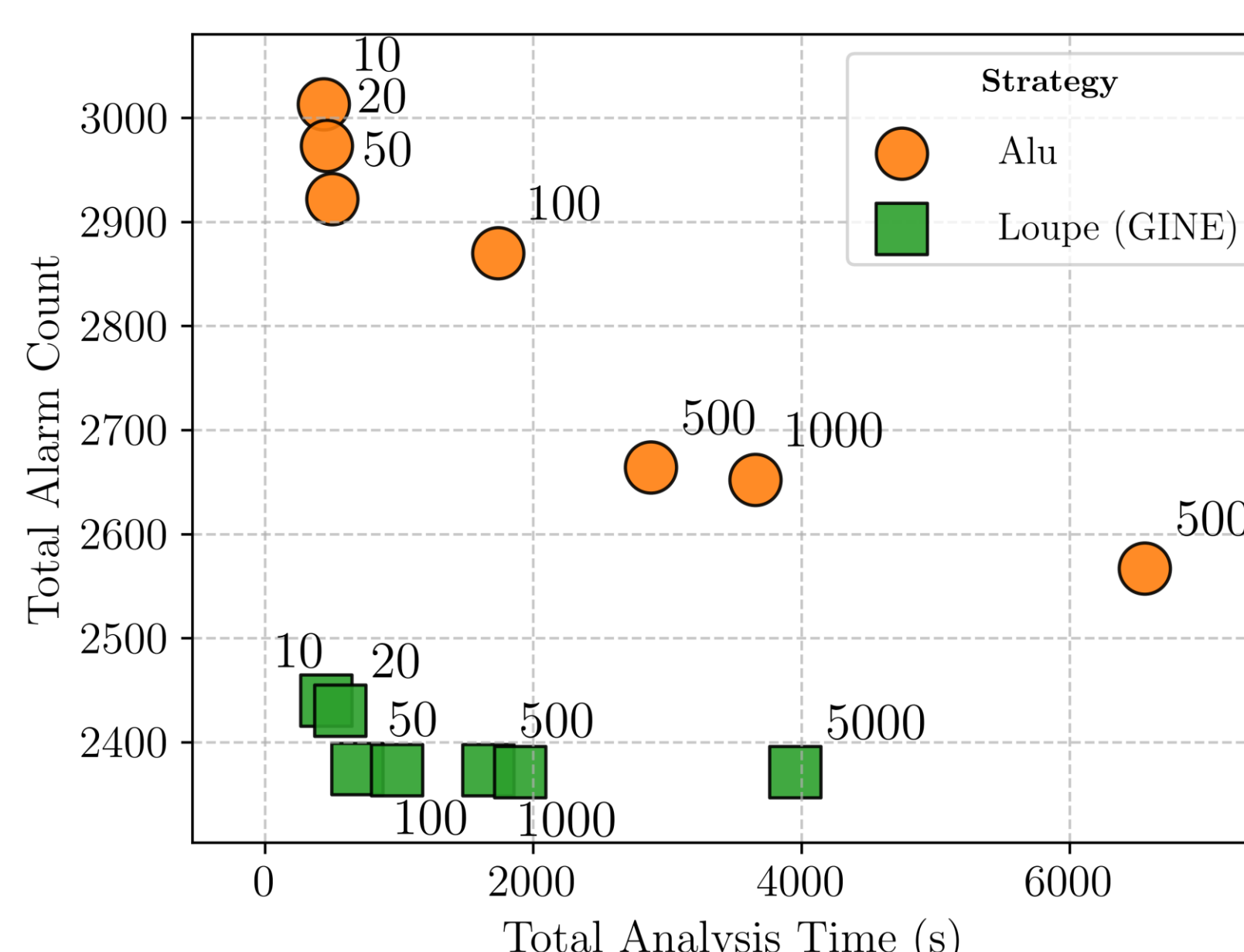
Model	ANGHABENCH (Test Split)					OSCS				
	P / R	F1	F2	B-ACC		P / R	F1	F2	B-ACC	
Random	8.4 / 50.3	14.3	25.1	50.1		11.5 / 48.2	18.6	29.5	49.2	
XGBOOST- IR2VEC	28.3 / 33.5	30.7	32.3	62.7		54.9 / 14.7	23.2	17.2	56.3	
SVM- SPARROW	8.2 / 88.6	15.0	29.9	49.2		7.2 / 41.3	12.3	21.3	35.1	
GRAPHCODEBERT	20.4 / 81.8	32.7	51.1	76.6		23.3 / 80.7	36.1	54.0	66.2	
DGCNN	24.3 / 79.3	37.4	54.8	78.7		21.7 / 50.8	26.6	34.70	58.3	
GAT	22.8 / 73.6	35.6	52.2	76.7		21.8 / 68.7	31.1	51.27	66.7	
GIN	11.1 / 77.1	34.8	52.1	76.9		23.1 / 49.1	33.4	48.95	67.0	
GINE	26.8 / 81.6	40.4	57.98	80.85		26.9 / 79.1	40.1	57.01	70.06	

## Performance & Generality

### RQ2:



☐ Loupe (GINE) vs Alu with varying unrolling factors – Fig.4



### RQ3:

☐ TABLE II

- Loupe (GINE) trained on Frama-C/Eva **improved** Mopsa performance
- Retraining on Mopsa's data achieved **75%** of T's alarm reduction
- The Mopsa model ran **6.5x** faster than T

## Key Takeaways

- ✓ **Effective:** >25% improvement in F2 score over feature-engineered methods
- ✓ **Precise & Efficient:** Reduces false alarms by a factor of 1.5 and improves analysis efficiency by >50% compared to built-in heuristics
- ✓ **Expert-Level Accuracy:** Matches >81% of expert loop unrolling annotations in Open Source Case Studies
- ✓ **Abstract Domains Consistency:** Loupe (GINE) maintains **uniform** alarm-reduction trends and **outperforms** Alu across all abstract domains.
- ✓ **Cross-Analyzer Generalization:** Successfully **transfers** from Frama-C/Eva to Mopsa, demonstrating **robust adaptability**