Eiffel: Inferring Input Ranges of Significant Floating-point Errors via Polynomial Extrapolation



Zuoyan Zhang, Bei Zhou, Jiangwei Hao, Hongru Yang, Mengqi Cui Yuchang Zhou, Guanghui Song, Fei Li, Jinchen Xu, and Jie Zhao

Information Engineering University

- What is floating-point error?
- Error detection is important
- Existing approaches



Floating-point Errors

- Some inputs may trigger significant FP errors
- Consider:

$$f(x) = \frac{\tan(x) - \sin(x)}{x^3} \qquad \lim_{x \to 0} f(x) = 0.5$$

double f(double x) {
double num = tan(x) - sin(x);
double den = x * x * x;
return num / den;

>>> f(1e-7) // 64 bits result 0.5029258124322410

Accurate result //128 bits result 0.5000000000000012

Error Detection is Crucial

• FP errors are infamous problem in software development



- Large rounding errors may lead to catastrophic software failures
 - Missile yaw [Skeel '92]
 - Stock trading disorder [Quinn '83]
 - Rocket launch failure [Lions '96]

Existing approaches



Static analysis

- Abstract interpretation
- Symbolic execution
- Interval arithmetic
- Affine arithmetic

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Goal: Approximate error bounds

- Over-approximated



Dynamic analysis

- Random search
- Binary guided random testing (BGRT)
- Atomic condition

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Goal: Find the maximal error + Real error



Difficulties for guided searches



Process

- Search space: $D = \{(x, y) : c_1 \land c_2 \land c_3\}$
- c₁, c₂, c₃ are constraints of the two variables x and y;
- The points within *r* are input values that may trigger significant errors;
- p is the input that triggers the maximal error.

Goal: Find the point p

Difficulties

- D may be complex and large
- r and p could both be many



Error analysis using EIFFEL

Core idea of EIFFEL: Inferring error-inducing ranges instead of searching them in D



Data set construction

Two issues

- Determine *R*
 - FP numbers are non-uniformly distributed
 - [-1,1] 49.95% (double type)
 - Dense near 0
- \implies Small interval as close to 0
- Deciding the number of input values *s* to compute the *ULP* errors, considers
 - Performance $\Rightarrow s = 500,000 (0.17 \text{ seconds})$
 - Accurate error distribution \Rightarrow Uniformly distributed inputs

Boundary extraction and data clustering

- Boundary extraction
 - Reduce the number of data points to accelerate clustering
 - Step 1: Gather every g = 500 samples in one group

Step 2: Preserve the one that has the largest *ULP* error in every group



• Data clustering

- Obtain the maximal error point for each cluster for fitting the function
 - DBSCAN clustering algorithm



Curve derivation and polynomial extrapolation

- Curve derivation
 - Two challenges
 - Each peak point is a 2D coordinate
 - Extrapolated points may still follow the same distribution as that of the stars
 - Solution
 - 2D coordinates into 1D form

 $(x_1, error_1), (x_2, error_2) \dots (x_i, error_i) \rightarrow (1, x_1), (2, x_2) \dots (i, x_i)$

• Assume the x_i form a geometric sequence or a geometric progression

$$x_i = x_1 \times q^{i-1} \qquad i \ge 1$$

The assumption is observed from extensive experiments

- Derive two curves
 - Best fit for lower bound x_i r and upper bound x_i + r that covers each x_i





Curve derivation and polynomial extrapolation

• Polynomial extrapolation



Error detection

- num = 1 or num = 2
 - Return maximal error across R



- $num \geq 3$
 - Consider the monotonicity
 - $error_1 < error_2 < \cdots$
 - $error_1 > error_2 > \cdots$



$$\frac{r_1}{\mathcal{D}}$$



Generalization for multi-variate scenarios

Similar to the single-variate case

- Two adaptations
 - Project the multi-dimensional plot onto the variable space

Produce the variable coordinates of the errors

• Perform curve fitting along one dimension each time

Produce (hyper-)rectangular ranges but is still more effective than existing approaches





Evaluation

- Benchmarks: total 70 expressions
 - 66 expressions are from FPBench
 - 4 expressions are from real-life numerical programs
- *D* is set using large but reasonable ranges

Total Benchmarks	Single-variate	Multi-variate
70	30	40

Evaluation — Effectiveness

- Effectiveness
 - Compared with the state-of-the-art techniques

Techniques	Number of errors detected	
EIFFEL	70	
S3FP	43	
ATOMU	30	

ATOMU is only able to report errors for the 30 single-variate examples

S3FP returns empty results for 27 benchmarks

Evaluation — Inferred input ranges

• Quantity

- Regina fails to infer input ranges at a large size of D
- EIFFEL obtains more input ranges than PSAT

• Quality

• Feed the inferred input ranges to Herbie

Improvement	Original Herbie version
Average	3.35 bits
Maximal	53.3 bits



Development	Number	
Вепсптагк	EIFFEL	PSAT
predatorPrey	15	2
sqrt_add	7	2
verhulst	12	2
nonlin1_test2	14	2
Intro-example	14	2
NMSEexample35	15	5
NMSEexample37	27	4
carbonGas	21	3

Evaluation — Overhead

Time overhead is between ATOMU and S3FP

