Programming with Numerical Uncertainties

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Programming

• implement a real-valued arithmetic function

def sine(x: ???): ??? = {

}

 $x - (x^*x^*x)/6.0 + (x^*x^*x^*x)/120.0 - (x^*x^*x^*x^*x^*x)/5040.0$



runtime



Programming

• implement a real-valued arithmetic function

- ... with Numerical Uncertainties
 - roundoff errors
 - input errors (e.g. measurement uncertainties)



Programming

• implement a real-valued arithmetic function

- ... with Numerical Uncertainties
 - roundoff errors
 - input errors (e.g. measurement uncertainties)
 - deliberate approximations (approximate computing)

... correctly

Outline

- a new programming model
- *estimating* errors soundly & accurately
 - nonlinearity
 - discontinuities
 - loops
- *improving* accuracy

A Real-Valued Spec

def sine(x: Real): Real = {

}

 $x - (x^*x^*x)/6.0 + (x^*x^*x^*x)/120.0 - (x^*x^*x^*x^*x)/5040.0$

A Real-Valued Spec



A Real-Valued Spec

- def sine(x: Real): Real = {
 require(x > -1.57079632679 && x < 1.57079632679 && x +/- 1e-11)
 x (x*x*x)/6.0 + (x*x*x*x*x)/120.0 (x*x*x*x*x*x)/5040.0</pre>
- } ensuring(res => res +/- 1.001e-11)

- what a scientist has on paper/in mind
- what you may have proven correct
- ideal baseline
- allows compiler optimisations

Rosa - the Verifying Compiler

> Float Double DoubleDouble QuadDouble

def sineWithError(x : Long): Long = {
 require(-1.5707963268 <= x && x <= 1.5707963268)
 val _tmp1 = ((x * x) >> 31)
 val _tmp2 = ((_tmp1 * x) >> 30)
 val _tmp3 = ((_tmp2 << 30) / 16106127361)
 val _tmp4 = ((x << 1) - _tmp3)
 val _tmp5 = ((x * x) >> 31)
 val _tmp6 = ((_tmp5 * x) >> 30)
 val _tmp7 = ((_tmp6 * x) >> 31)
 val _tmp8 = ((_tmp7 * x) >> 31)
 val _tmp9 = ((_tmp8 << 28) / 20132659201)
 val _tmp10 = ((_tmp4 + _tmp9) >> 1)

Rosa - the Verifying Compile

def sine(x: Real): Real = {
 require(x > -1.57079632679 && x < 1.57079632679 && x +/- 1e-11)</pre>

 $x - (x^*x^*x)/6.0 + (x^*x^*x^*x)/120.0 - (x^*x^*x^*x^*x)/5040.0$



State of the Art

quantifying numerical errors

- numerical analysis [e.g. Higham'02]
 - manual analysis by expert
- interactive theorem proving [e.g. in Coq: Boldo'11]
 - partly manual, requires expert guidance
- testing [Benz'12, Chiang'14, Paganelli'13, ...]
 - gives no strong guarantees
- static analysis
 - automated, with guarantees and reasonable accuracy

Quantifying Numerical Errors

Goal: statically, soundly, accurately and automatically

Quantifying Numerical Errors in loop-free, branch-free code

Sound absolute error bound:

- worst-case roundoff errors
- worst-case error propagation
 - both depend on the ranges

for each arithmetic operation

- 1. compute *real* range for intermediate value
- 2. propagate existing errors
- 3. compute new roundoff error

Standard Range Arithmetic

• interval arithmetic

$$x \in [-a, a]$$

 $x - x = [-a, a] - [-a, a] = [-2a, 2a]$

• affine arithmetic (AA)

$$\hat{x} = x_{\circ} + \sum_{i=1}^{n} x_i \epsilon_i, \ \epsilon_i \in [-1, 1]$$
 $x \in \left[x_{\circ} - \sum_{i=1}^{n} |x_i|, \ x_{\circ} + \sum_{i=1}^{n} |x_i| \right]$

$$x - x = x_{\circ} + a\epsilon_1 - (x_{\circ} + a\epsilon_1)$$
$$= x_{\circ} - x_{\circ} + a\epsilon_1 - a\epsilon_1 = 0$$

nonlinear operations have to be approximated





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Challenges:

- nonlinearity
 - range estimation
 - error computation & propagation

Interval arithmetic meets SMT

Use Z3's nonlinear solver:

for every computation step

- get initial range with interval arithmetic
- refine bounds with binary search with Z3

- includes any correlations between variables
- includes additional constraints
- includes runtime error checks (overflow, div-by-zero, ...)

selected Experiments comparing computed normalised interval width



$$|f(x) - \tilde{f}(\tilde{x})|$$

total error





affine arithmetic

Tracking Roundoff Errors

with affine arithmetic

$$\hat{x} = x_{\circ} + \sum_{i=1}^{n} x_i \epsilon_i \qquad \epsilon_i \in [-1, 1]$$

for each arithmetic operation

- propagate existing x_i 's
- add a new x_{n+1} for the new roundoff error determined according to finite-precision format

Error Propagation

|f(x) - f(y)|

Error Propagation

based on Lipschitz continuity

$$|f(x) - f(y)| \le K|x - y| \qquad \qquad K_i = \sup_{x,y} \frac{\partial f}{\partial w_i}$$

- constants K_i capture maximum steepness of f
 - ability to magnify errors
- partial derivatives computed symbolically
- bounded with Z3-based range computation
 - automatic

require(-5 <= x && x <= 5 && -20 <= y && y <= 5 &&
 x +/- 1e-11 && y +/- 1e-11)</pre>

val t =
$$(3*x*x + 2*y - x)$$

val t2 = $x*x + 1$
val t2 = $x*x + 1$
val t2 = $x*x + 1$
val t2 = $x*x + 1$

both affine arithmetic and Lipschitz continuity introduce over-approximations

- AA is fine for small errors, for shorter computations
- derivatives most useful on larger expressions

The 'Competition'

Fluctuat

- developed concurrently
- AA-based
- constraints on affine terms
- interval subdivision

FPTaylor

- Taylor approximation wrt. errors
- optimisation-based
- transcendentals
- certificates

Real2Float



Conclusions

- for straight-line code, differences are small
- three tools, three implementations
- different (asymptotic) limitations:
 - Rosa: SMT solver may time-out unpredictably
 - Fluctuat: predictable times, but accuracy may deteriorate
 - FPTaylor: potentially large running time with constraints

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Challenges:

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Discontinuities

- - if (y < x)
 -0.317581 + 0.0563331*x + 0.0966019*x*x + 0.0132828*y +
 0.0372319*x*y + 0.00204579*y*y</pre>

else

}

-0.330458 + 0.0478931*x + 0.154893*x*x + 0.0185116*y -0.0153842*x*y - 0.00204579*y*y

What happens

when the real and the finite precision computation take different paths?

Discontinuity Error if (c) f1 else f2

 $|f_1(x) - \tilde{f}_2(\tilde{x})|$

Discontinuity Error if (c) f1 else f2

separation of errors:



real-valued difference between branches



Quantifying Numerical Errors

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Challenges:

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 - range estimation
 - error computation & propagation
- discontinuities
- loops



- numerical errors in general grow without bound
- one possible strategy: unrolling
- our strategy (for some loops):

compute error as function of # iterations

g : propagation error **σ** : roundoff error

$$|f^m(x) - \tilde{f}^m(\tilde{x})|$$

g : propagation error **σ** : roundoff error

$$|f^{m}(x) - \tilde{f}^{m}(\tilde{x})| \leq g^{m}(|x - \tilde{x}|) + \sum_{i=0}^{m-1} g^{i}(\sigma(\tilde{f}^{m-i-1}(\tilde{x})))$$
propagation of
propagation of
initial error
propagation of
roundoff from each iteration

IF we can compute error propagation and roundoff globally

$$|f^{m}(x) - \tilde{f}^{m}(\tilde{x})| \leq K^{m}\lambda + ((I - K)^{-1}(I - K^{m}))\sigma$$

initial error propagation propagation over all iterations
40

```
def sine(x: Real): Real = {
  require(-5 <= x && x <= 5)
 x - x x x x / 6 + x x x x x x / 120
}
def pendulum(t: Real, w: Real, n: LoopCounter): (Real,Real) = {
  require(-2 <= t && t <= 2 && -5 <= w && w <= 5 &&
               -2.01 <= ~t && ~t <= 2.01 && -5.01 <= ~w && ~w <= 5.01)
  if (n < 1000) {
    val h: Real = 0.01
    val L: Real = 2.0
    val m: Real = 1.5
    val g: Real = 9.80665
    val k1t = w
    val k1w = -g/L * sine(t)
    val k2t = w + h/2*k1w
    val k_{2w} = -g/L * sine(t + h/2*k_{1t})
    val tNew = t + h*k2t
    val wNew = w + h*k2w
    pendulum(tNew, wNew, n + 1)
 } else {
    (t, w)
 }
}
```

```
def sine(x: Real): Real = {
 require(-5 <= x && x <= 5)
 x - x x x x / 6 + x x x x x / 120
}
def pendulum(t: Real, w: Real, n: LoopCounter): (Real,Real) = {
 require(-2 <= t && t <= 2 && -5 <= w && w <= 5 &&
              -2.01 <= -t \&\& -t <= 2.01 \&\& -5.01 <= -w \&\& -w <= 5.01
 if (n < 1000) {
                                                             assumption:
   val h: Real = 0.01
   val L: Real = 2.0
                                                          bounded ranges
   val m: Real = 1.5
   val g: Real = 9.80665
   val k1t = w
   val k1w = -g/L * sine(t)
   val k2t = w + h/2*k1w
                                                   for loop body
   val k_{2w} = -g/L * sine(t + h/2*k_{1t})
                                            1. analyse derivative
   val tNew = t + h*k2t
   val wNew = w + h*k2w
                                            2. compute new roundoff
   pendulum(tNew, wNew, n + 1)
                                            3. plug into
 } else {
   (t, w)
                                                closed-form expression
 }
```

```
def sine(x: Real): Real = {
  require(-5 <= x && x <= 5)
 x - x x x x / 6 + x x x x x x / 120
}
def pendulum(t: Real, w: Real, n: LoopCounter): (Real,Real) = {
  require(-2 <= t && t <= 2 && -5 <= w && w <= 5 &&
                -2.01 \le -1.01 \le -1.01 \le -1.01 \le -1.01 \le -1.01 \le -1.01 \le -1.01
  if (n < 1000) {
    val h: Real = 0.01
    val L: Real = 2.0
    val m: Real = 1.5
    val g: Real = 9.80665
                                                                Fluctuat
                                                # iterations
                                                                              Our tool
    val k1t = w
                                                               (unrolling)
    val k1w = -g/L * sine(t)
    val k2t = w + h/2*k1w
    val k_{2w} = -g/L * sine(t + h/2*k_{1t})
                                                                 2.43e-13
                                                                                2.21e-14
                                                     50
    val tNew = t + h*k2t
    val wNew = w + h*k2w
                                                     100
                                                                               8.82e-14
                                                                   \infty
    pendulum(tNew, wNew, n + 1)
  } else {
                                                                               2.67E-12
                                                    250
                                                                   \infty
    (t, w)
  }
                                                    500
                                                                               6.54E-10
}
                                                                   \infty
```

(time: 8s)

Quantifying Numerical Errors

Goal: statically, soundly, accurately and automatically

Challenges:

- nonlinearity
 - range estimation
 - error computation & propagation
- discontinuities
- loops

Quantifying Numerical Errors

Goal: statically, soundly, accurately and automatically

Key Ideas:

- separation of errors
- combine interval/affine arithmetic with SMT
- use derivatives with SMT

Finite-Precision is Non-Associative

Previous technique assumed fixed computation order.

error determined by simulation

(-0.0078)*st1+0.9052*st2 +(-0.0181)*st3 + (-0.0392)*st4 +(-0.0003)*y1+0.0020*y2

3.06e-3

exploit non-associativity

((0.9052*st2)+(((st3*-0.0181) +(-0.0078*st1))+ (((-0.0392*st4) +(-0.0003*y1))+(0.002*y2))))

1.39e-3

Synthesizing Accurate Expressions [E. Darulova, V. Kuncak, R. Majumdar and I. Saha, EMSOFT'13]

- enumerating all expressions is infeasible
- small local error can produce large global error
- genetic programming as search strategy:
 - genetic algorithm over AST (instead of strings)
 - 30 generations with a population of 30
 - mutation: associativity, distributivity, etc.
 - crossover: labeling
 - fitness function: static analysis, AA-based

Static Analysis as Fitness Function





Guarantees

- no optimality
 - incomplete search
 - static, over-approximating analysis may not discriminate correctly

find expression with <u>provable</u> smallest bound

Evolution of Errors



selected Experiments

improvement over automatically generated initial version



The 'Competition'

[Martel'09, Ioualalen&Martel'12]

- abstract domain to represent under-representation of possible rewritings
- local search
- optimise bit-length

[Eldib&Wang'13]

- SMT-base synthesis with skeleton
- linear expressions only
- local search

Herbie [PLDI'15]

- testing-based heuristic search
- average error
- 'regime' inference

Conclusion

Quantifying numerical uncertainties is hard.

Combination of techniques + advances in SMT automated & accurate results

- nonlinearity, branches and loops
- non-associativity

Thank you!