# Probability Type Inference for Flexible Approximate Programming 

Brett Boston ${ }^{1}$ Adrian Sampson ${ }^{2}$ Dan Grossman ${ }^{3} \quad$ Luis Ceze ${ }^{3}$
${ }^{1}$ MIT $\quad{ }^{2}$ Cornell $\quad{ }^{3}$ University of Washington
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## Approximate Computing

- Not every operation in a program has to be correct
- Possible to save energy and execution time


## Motivation

- Programmer indicates what operations may be approximated and to what degree
- Hardware allows specification of each arithmetic operator
- Hard to choose right level of approximation for each arithmetic operation in a program

```
int a = 1 +0.95 4
int b = 4 +0.99 a
int z = y +o.9 v
```


## Approach

- We'd like to allow the programmer to bound reliability and let the compiler figure out operator correctness
- Our approach frames problem as one of type inference and uses an SMT solver to solve it


## Outline

- Basic Approximate Programming Language
- Probability Type Inference
- Hardware Model


## All-or-Nothing Approximation

- Type annotations on variables
- Built our system on EnerJ

```
@Approx int a = 1;
@Approx int b = 2;
@Approx int c=a + b; // + is approximate
@Precise int p; // @Precise is unnecessary here
p = c; // Illegal
p = endorse(c); // Casts c to a precise int
```

- Endorse is unsound


## All-or-Nothing Approximation

What if we want more than all-or-nothing approximation?

- We need something more descriptive
- We have hardware that can support more than two degrees of reliability


## Enter: The Paramaterized @Approx Annotation

©Approx(n)
At any point in the execution, the probability that the value is correct is at least $n$.

Correct The value is the same as it would be during fully precise execution.

## @Approx(n) Rules: Subtyping

```
@Approx(0.9) int a = 1; // legal
@Approx(0.9) int b = a; // legal
@Approx(0.5) int c = a; // legal
@Approx(0.95) int d = a; // illegal
```

Let $\prec$ denote a subtyping relationship between qualified types $q \tau$, then

$$
\frac{x \geq y}{@ \operatorname{Approx}(\mathrm{x}) \tau \prec \text { @Approx }(\mathrm{y}) \tau}
$$

## @Approx(n) Rules: Binary Operators

```
@Approx(0.9) int x = 1;
@Approx(0.9) int y = 2;
@Approx(0.81) int a = x + y;
@Approx(0.7) int b = x + y;
```

- $x+y$ is correct with probability at least 0.81 , given + is precise
- Follows from product rule; $\mathrm{P}(A \cap B) \geq \mathrm{P}(A) \times \mathrm{P}(B)$
- Values approximated through imprecise binary operations


## Language Details

- Conservatively treat all values as independent.
- Control flow only allowed on precise values.


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## Problem: Annotation Burden

I have a complex function I'd like to annotate, and I know how precise I'd like the inputs and outputs to be. How should I go about annotating the innards?

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Answer: Guess, get errors, repeat.
Answer: Type inference!

## Solution: Type Inference

## Inputs

@Approx(n) explicit annotations

- Indicate probability should be inferred by leaving off parameter.
- Reliability of binary operators


## Innards

@Approx inferred annotations

## Outputs

@Approx(n) explicit annotations implicitly inferred such that the expression's reliability minimized as much as possible while still satisfying reliability guarantees.

- Developers use @Approx(n) where they have quality requirements.

```
// Approximate area of triangle
@Approx float base = ...;
@Approx float height = ...;
@Approx(0.9) float area = base * height / 2;
```


## Inferring Probability Types



## Inferring Probability Types Example

```
(declare-const op1 Real)
(assert (>= op1 0.0))
(assert (<= op1 1.0))
(declare-const x Real)
(assert (>= x 0.0))
(assert (<= x 1.0))
(declare-const y Real)
(assert (>= y 0.0))
(assert (<= y 1.0))
(declare-const z Real)
(assert (= z 0.81))
(assert (<= z (* x y op1)))
```

- One solution to this is $x=y=0.9, o p 1=1.0$
- Z3 arbitrarily selects $x=\frac{15}{16}, y=\frac{127}{128}, o p 1=\frac{7}{8}$
- Optimal result is $x=y=1.0$, op $1=0.81$


## Objective Function

- Average inferred probabilities across a function, targeting a specific average reliability.
- We can approach an optimal result using a linear search.
- Lower target reliability by a constant amount until problem is unsatisfiable, or times out.


## Objective Function Example

```
@Approx(0.81) int z = a + b + c;
```

(declare-const obj-target Real)
(assert (= obj-target (/ (+ op1 op2) 2)))
(assert (<= obj-target 1.0))
(check-sat)
sat
(push)
(assert (<= obj-target 0.99))
(check-sat)
sat
. . .
(push)
(assert (<= obj-target p))
(check-sat)
unsat
( $p \circ p$ )

## Method Specialization

- Methods specialized for each invocation
- Interprocedural
- Detects cycles in call structure
- Programmer can bound number of times a method will be specialized

```
void example() {
    @Approx(0.9) area1 = triArea(1, 2);
    @Approx(0.95) area2 = triArea(1, 3);
}
@Approx float triArea(@Approx float b,
                                @Approx float h) {
    @Approx float c;
    c = b * h / 2;
    return c;
}
```


## @Dyn Types

- @Dyn types track reliability at runtime.
- Dynamic cast back to @Approx(n) with checked_endorse.

```
@Approx int[] nums = ...;
@Dyn int sumD = 0;
for (@Approx int num : nums)
    sumD += num;
@Approx int sum = checked_endorse(sumD, 0.9);
```


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## Hardware Simulation

- Z3 exports operator reliability for each operator
- Instrumentation pass replaces operators with calls to custom function in simulator
- Simulator performs approximate operations and records statistics


## Discrete Reliability Levels

- Realistically, most hardware will not have continuous operation reliability knobs.
- Allow programmer to specify discrete levels at compile time, or run time


## Discrete Reliability Level Constraints

$\$$ enerjc prog.java -Alevels $=0.9,0.99,1.0$
(declare-const op Real)
(assert (or (= op 0.9)
( $=$ op 0.99)
(= op 1.0)))

## Benchmarks

- EnerJ benchmarks
- Constrained inputs and outputs
- 344 LOC - 13180 LOC
- Few annotations needed to achieve approximation
- Overall outputs constrained to @Approx(0.9).

| Application | Description | Build Time | LOC | @Approx | @Approx(p) | @Dyn | Approx | Dyn |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| fft | Fourier transform | 2 sec | 747 | 37 | 11 | 23 | $7 \%$ | 55\% |
| imagefill | Bar code recognition | 14 min | 344 | 76 | 20 | 0 | 45\% | $<1 \%$ |
| lu | LU decomposition | 1 min | 775 | 63 | 9 | 12 | 24\% | $<1 \%$ |
| mc | Monte Carlo approximation | 2 min | 562 | 67 | 8 | 6 | 21\% | $<1 \%$ |
| raytracer | 3 D image reading | 1 min | 511 | 38 | 4 | 2 | 12\% | 44\% |
| smm | Sparse matrix multiply | 1 min | 601 | 37 | 4 | 4 | 28\% | 28\% |
| sor | Successive over-relaxation | 19 min | 589 | 43 | 3 | 3 | 63\% | $<1 \%$ |
| zxing | Bar code recognition | 16 min | 13180 | 220 | 98 | 4 | 31\% | $<1 \%$ |

## Operator Probabilities for n Discrete Levels



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## Also in the Paper

- Formal semantics
- Compiler warnings
- Results on solving versus rounding with discrete reliability levels
- Available at http://sampa.cs.washington.edu/decaf


## Future Work

Modularity Methods are effectively "inlined" for the purpose of type-checking. We could solve this by storing reliability of the return value in terms of the reliability of function arguments.

- Similar to Rely's system. [Carbin et al. 2013]

Error messages Errors in inference tell you only that an error exists somewhere in the method.

## Summary

- Language abstraction over flexible approximate hardware supporting multiple degrees of approximation.
- Low annotation burden leveraging type inference.
- Hope to inform hardware community.

