Microsoft

Safely Supporting Probabilistic Data: PL Techniques as Part of the Story

Dan Grossman
University of Washington

Microsoft Research
Faculty Summit
2015
July 8-9, 2015

Executive summary

- Language design+implementation to help wrangle uncertainty
  - PL concepts+tools are a *huge* help
  - But *also* need to learn from statisticians
  - ➢ Validate these claims with UW's *approximate computing* work

Acknowledgments: 9 co-authors [papers at end]
  - Especially Adrian Sampson, Luis Ceze
  - Including Kathryn and Todd

Background (1/2): PL bread-and-butter

Types for information flow

```
int<H> x;
int<L> y;
if(x)
  y = 7;
```

✗

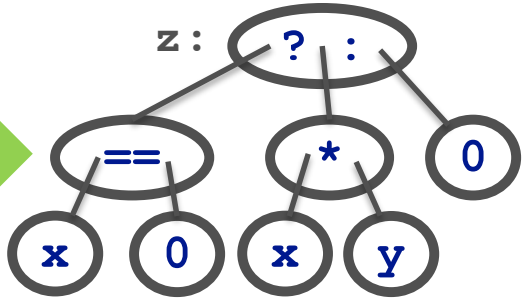
Type inference

```
let f = λ y. y+7
let z = f 9
let q = z && true
```

✗

Symbolic execution

```
z = x;
if(x!=0)
  z = x*y;
```



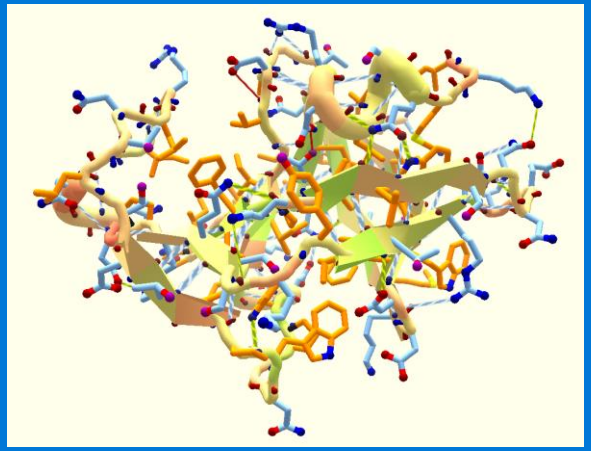
Function inlining/specialization

```
int f(int x, int y){
  return x*y;
}
f(0,a)
f(3,b)
f(1,c)
```

```
0
f(3,b)
c
```

Background (2/2): Approximation

- Full bit-precision is unnecessary and wastes energy



- Allowing probabilistic [in]correctness can work!
  - Let ALUs and memory produce garbage with low-nonzero probability
  - But most code/programmers want nothing to do with that…

EnerJ (and EnerC) a la 2011

Information flow is *exactly* the right high-level abstraction

- Type qualifier for **`@approx`**
- Explicit **`endorse`** as needed

- Convenient:
  - Opt-in with precise default
  - Overloaded operations and methods
- Strong guarantee: Approximate data has no effect on precise data except via **`endorse`** (classic *non-interference theorem*)

```
@approx int x = 12;
int y = 27;
y = x*2;
x = y*3;
@approx int z = f(x);
if(looks_okay(z))
  int w = endorse(z);
  …
```

EnerJ limitations

1. Only “best effort” semantics for approximate computation
   - Encapsulated all the probability, and then ignored it!

$$\frac{{}^{r}\Gamma \vdash h, e \rightsquigarrow h', v \qquad h' \cong \tilde{h}' \qquad v \cong \tilde{v}}{{}^{r}\Gamma \vdash h, e \rightsquigarrow \tilde{h}', \tilde{v}}$$

2. No approximate control-flow (without **`endorse`**)
   - Stronger limitation to ensure non-interference, no crashes, no extra non-termination, …

Adding probabilities (2015)

Address limitation #1 directly:

- **`@approx<p> int`:** static guarantee that at run-time value will be correct with *at least* probability **`p`**
- Operator uses (e.g., +) also have correctness probability

- EnerJ's **`@approx`** is **`@approx<0.0>`**
- Precise is **`@approx<1.0>`**
- Natural subtyping: **`@approx<p> t <: @approx<q> t`** if **`p >= q`**

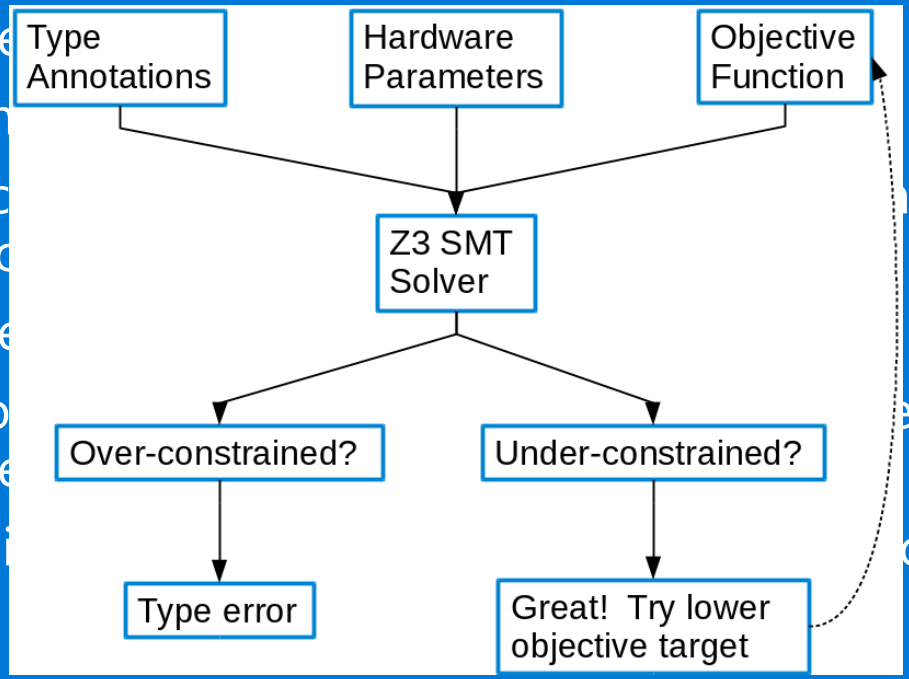
[See also Mike's Rely and Chisel work (2014)]

Essential additions

Type inference

- Programm puts, outputs)
- Automatic mer can provide more anno

- Type inference
  - Problem o e as much energy as possible
  - We use Mi ctive function



Essential additions

- Type inference, part 1:
  - Programmer states probabilities at key points (inputs, outputs)
  - Automatic solver fills in the rest, and/or programmer can provide more annotations
- Type inference, part 2:
  - Problem often under-constrained; goal is to save as much energy as possible within constraints
  - We use Microsoft's Z3 solver with a custom objective function

Method specialization

  - Up to *k* approximation settings for each method
- Opt-in dynamic tracking for loop-carried dependencies

Still not much statistics

- Additions are all "PL bread-and-butter"
- Uses only one trivial statistical fact:

```
@approx<p1> int x = …;
@approx<p2> int y = …;
x +<p3> y // @approx<p1*p2*p3>
```

  - Result type is *precise* if x, y, (and addition) are independent
  - Result type is *sound* regardless of [in]dependence

- Other panelists all make much better use of statistics, like in our *probabilistic assertions* work…

Probabilistic assertions (2014)

Much richer setting:

- Inputs/values can have arbitrary distributions, not just “Bernouilli failure”

- Dependence tracked via symbolic execution, even through if-statements and some loops
- Evaluate arbitrary probabilistic assertions:

```
passert(e,p,c)
```

Key insight:

- Data-structure produced by symbolic execution is an “expression DAG” *and* a “Bayesian network”
- So apply compiler *and* statistical optimizations to it
  - Followed by hypothesis testing

The limitation

- EnerJ and follow-on work gave *static guarantees* regardless of input
- Probabilistic assertions either revalidates for each input (*testing*) or needs probabilistic assumptions *(distributions) of inputs*
- Need more research on:
  - Bridging this gap
  - Supporting unbounded loops by soundly trimming low-probability paths

The big context

- "Early days"
  - Excited by the panel's work, but many open questions…
  - *Technical* questions: (loops, modularity, scale, …)
  - *Tools* questions, also with some preliminary work
    - Debugging, profiling, monitoring
    - Error messages

- Is "adding statistical properties" to modern language design The True Way Forward or a local optimum to avoid?

To learn more

- *EnerJ: Approximate Data Types for Safe and General Low-Power Computation.* Adrian Sampson, Werner Dietl, Emily Fortuna, Danushen Gnanapragasam, Luis Ceze, Dan Grossman. PLDI2011

- *Expressing and Verifying Probabilistic Assertions*. Adrian Sampson, Pavel Panchekha, Todd Mytkowicz, Kathryn S. McKinley, Dan Grossman, Luis Ceze. PLDI2014

- *Probability Type Inference for Flexible Approximate Programming.* Brett Boston, Adrian Sampson, Dan Grossman, Luis Ceze. OOPSLA 2015