

# Scalable Precision Tuning of Numerical Software

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# Floating-Point Precision Tuning

- Reasoning about floating-point programs is difficult
  - Large variety of numerical problems
  - Most programmers not expert in floating point

- Common practice: use highest available precision

– Disadvantage: more expensive!

- Automated techniques for tuning precision

Given : *Accuracy Requirement*

Action: *Reduce precision*

Goal : *Accuracy and/or Performance*



# Precision Tuning Example

```
1 long double fun(long double p) {
2 long double pi = acos(-1.0);
3 long double q = sin(pi * p);
4     return q;
5 }
6
7 void simpsons() {
8 long double a, b;
9 long double h, s, x;
10 const long double fuzz = 1e-26;
11 const int n = 2000000;
12 ...
18 L100:
19     x = x + h;
20     s = s + 4.0 * fun(x);
21     x = x + h;
22     if (x + fuzz >= b) goto L110;
23     s = s + 2.0 * fun(x);
24     goto L100;
25 L110:
26     s = s + fun(x);
27     ...
28 }
```

Original Program



Tuned Program

Error threshold  $10^{-8}$

# Precision Tuning Example

```
1 long double fun(long double p) {
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24     goto L100;
25 L110:
26     s = s + fun(x);
27     ...
28 }
```

Original Program

```
1 long double fun(double p) {
2 double pi = acos(-1.0);
3 long double q = sinf(pi * p);
4     return q;
5 }
6
7 void simpsons() {
8 float a, b;
9 double s, x; float h;
10 const long float fuzz = 1e-26;
11 const int n = 2000000;
12 ...
21     x = x + h;
22     if (x + fuzz >= b) goto L110;
23     s = s + 2.0 * fun(x);
24     goto L100;
25 L110:
26     s = s + fun(x);
27     ...
28 }
```

Tuned Program

Tuned program runs 78.7% faster!

# Challenges in Precision Tuning

- Searching efficiently over variable types and function implementations
  - Naïve approach → exponential time
    - $2^n$  or  $3^n$  where  $n$  is the number of variables
  - Global minimum vs. a local minimum
- Evaluating type configurations
  - Less precision → not necessarily faster
  - Based on run time, energy consumption, etc.
- Determining accuracy constraints
  - How accurate must the final result be?
  - What error threshold to use?

# Precision Tuning Approaches

- Reducing precision vs. improving performance
  - Different objectives
- Dynamic vs. static approaches
  - *Dynamic*: Performed at runtime, requires program inputs, handles larger and more complex code, no guarantees for untested inputs
  - *Static*: Analyzes program without running it, limitations with certain program structures (e.g., loops), formal guarantees for analyzed code
- Instructions vs. variables vs. function calls
  - Various granularities of program transformation
  - Different scopes
- Binary vs. IR vs. source code
  - Tradeoff between granularity of transformation and tool usability

# Dynamic Tools for Precision Tuning

Precimonious

- Dynamic Analysis for Precision Tuning
  - Black-box approach to systematically search over variable types and functions

HiFPTuner

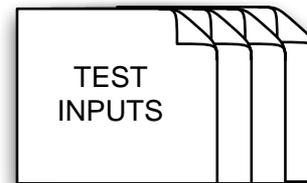
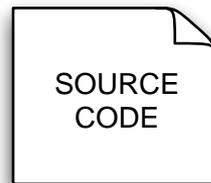
- Hierarchical Precision Tuner
  - Leverages relationship among variables to reduce search space and number of runs

# PRECIMONIOUS

*Dynamic Analysis for Floating-Point Precision Tuning*

<https://github.com/ucd-plse/precimonious>

Annotated with  
error threshold

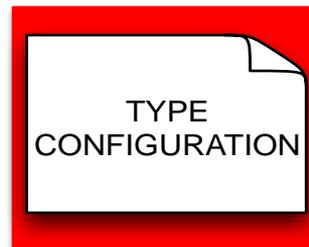


Search over types of variables  
and function implementations

Less Precision



Speedup



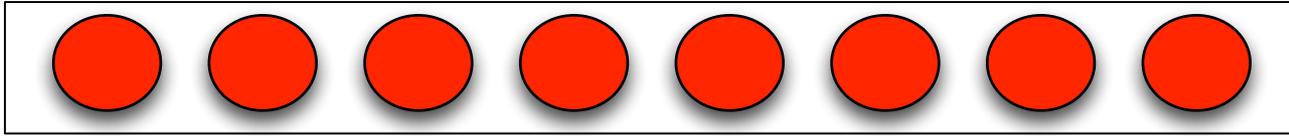
Result within error threshold  
for all test inputs

# Search Algorithm

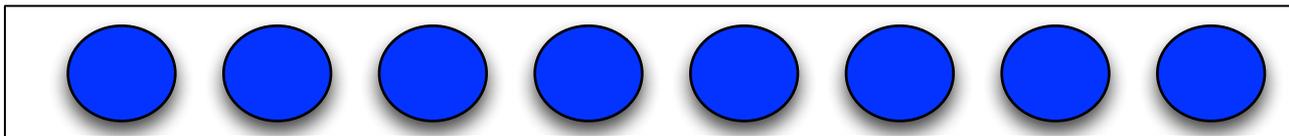
- Based on the Delta-Debugging Search Algorithm [1]
- Change the types of variables and function calls
  - Examples: double  $x \rightarrow$  float  $x$ ,  $\sin \rightarrow \text{sinf}$
- Our success criteria
  - Resulting program produces an “accurate enough” answer
  - Resulting program is **faster** than the original program
- Main idea
  - Start by associating each variable with set of types
    - Example:  $x \rightarrow \{\text{long double, double, float}\}$
  - Refine set until it contains only one type
- Find a local minimum
  - Lowering the precision of one more variable violates success criteria

# Searching for Type Configuration

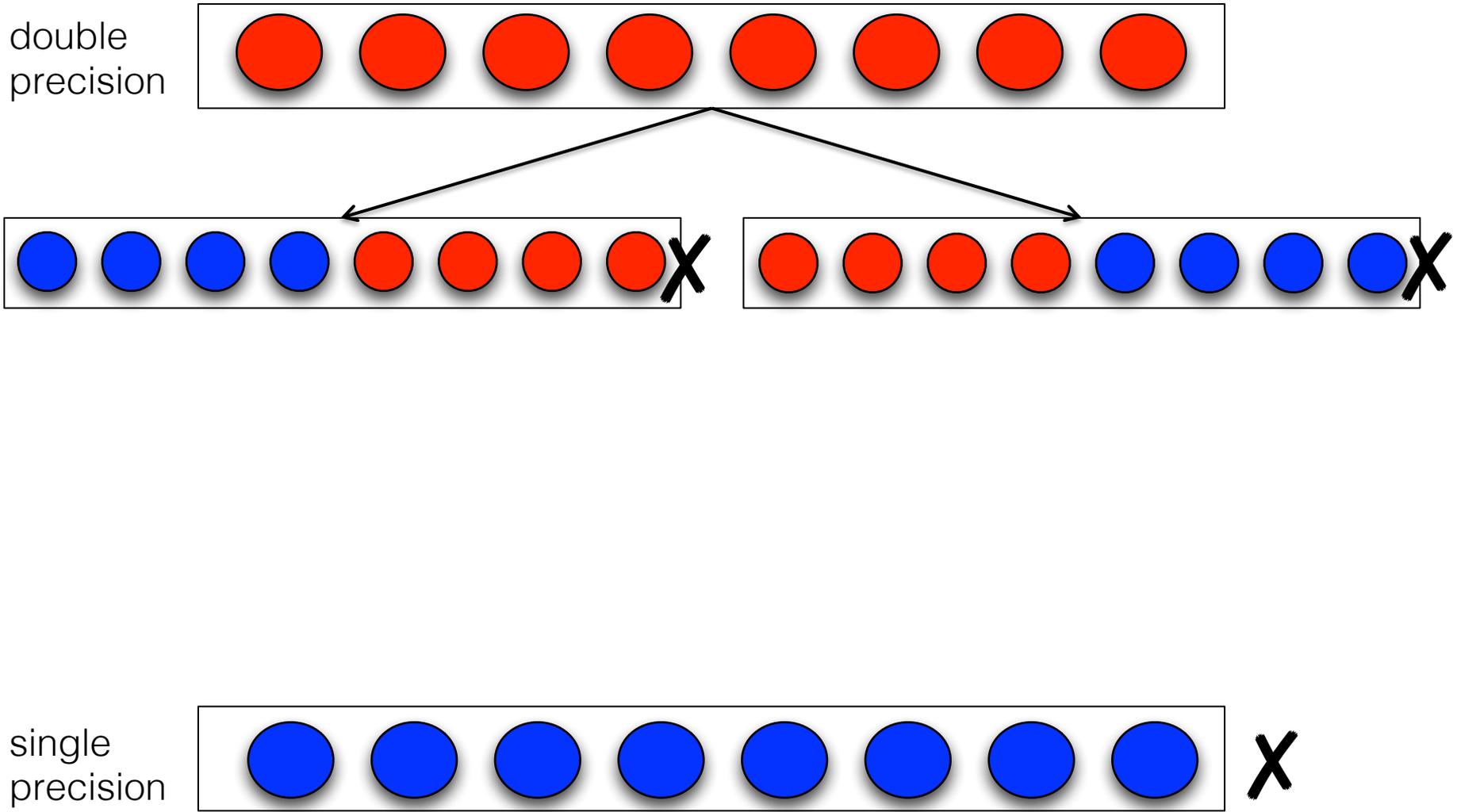
double  
precision



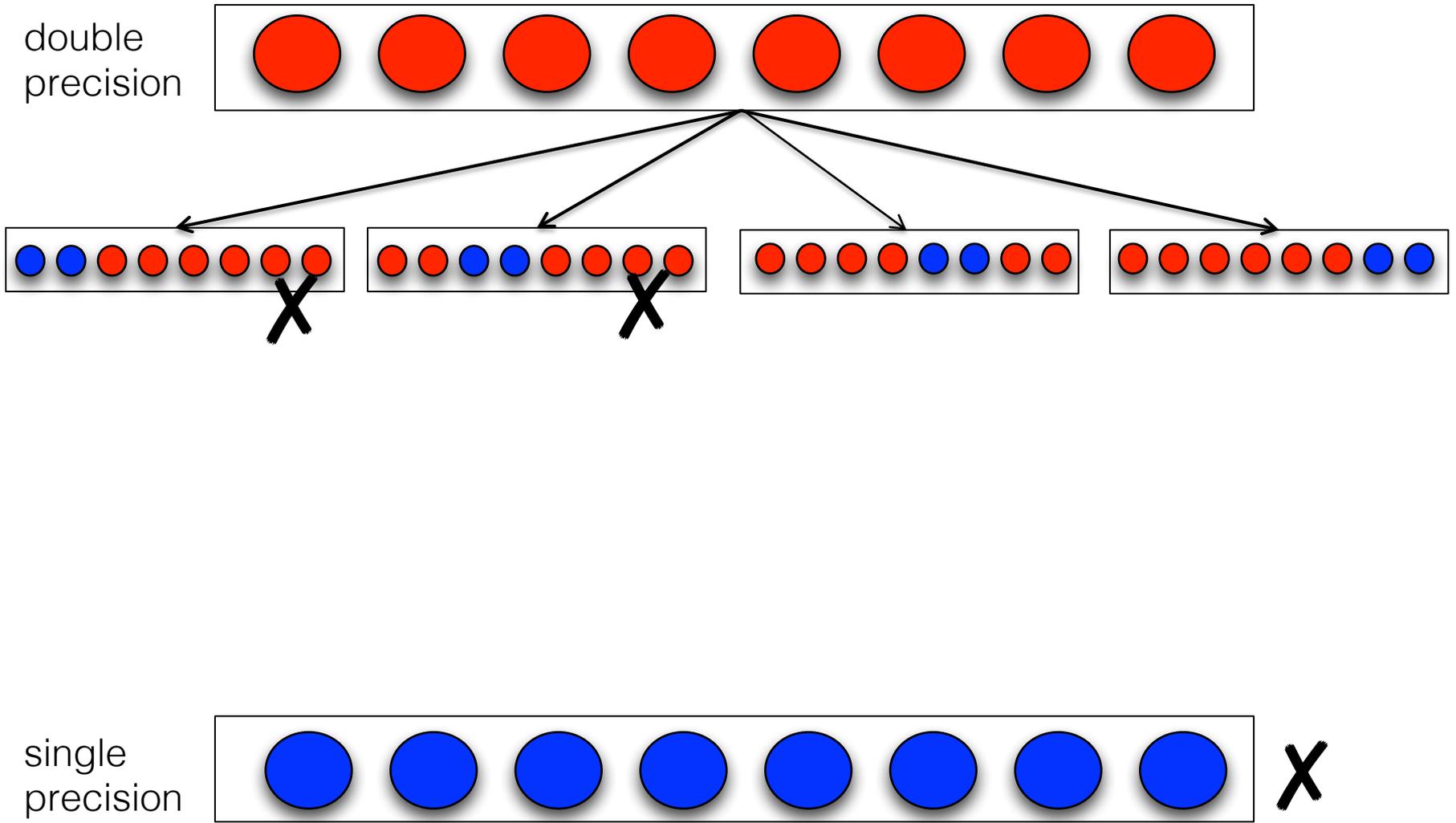
single  
precision



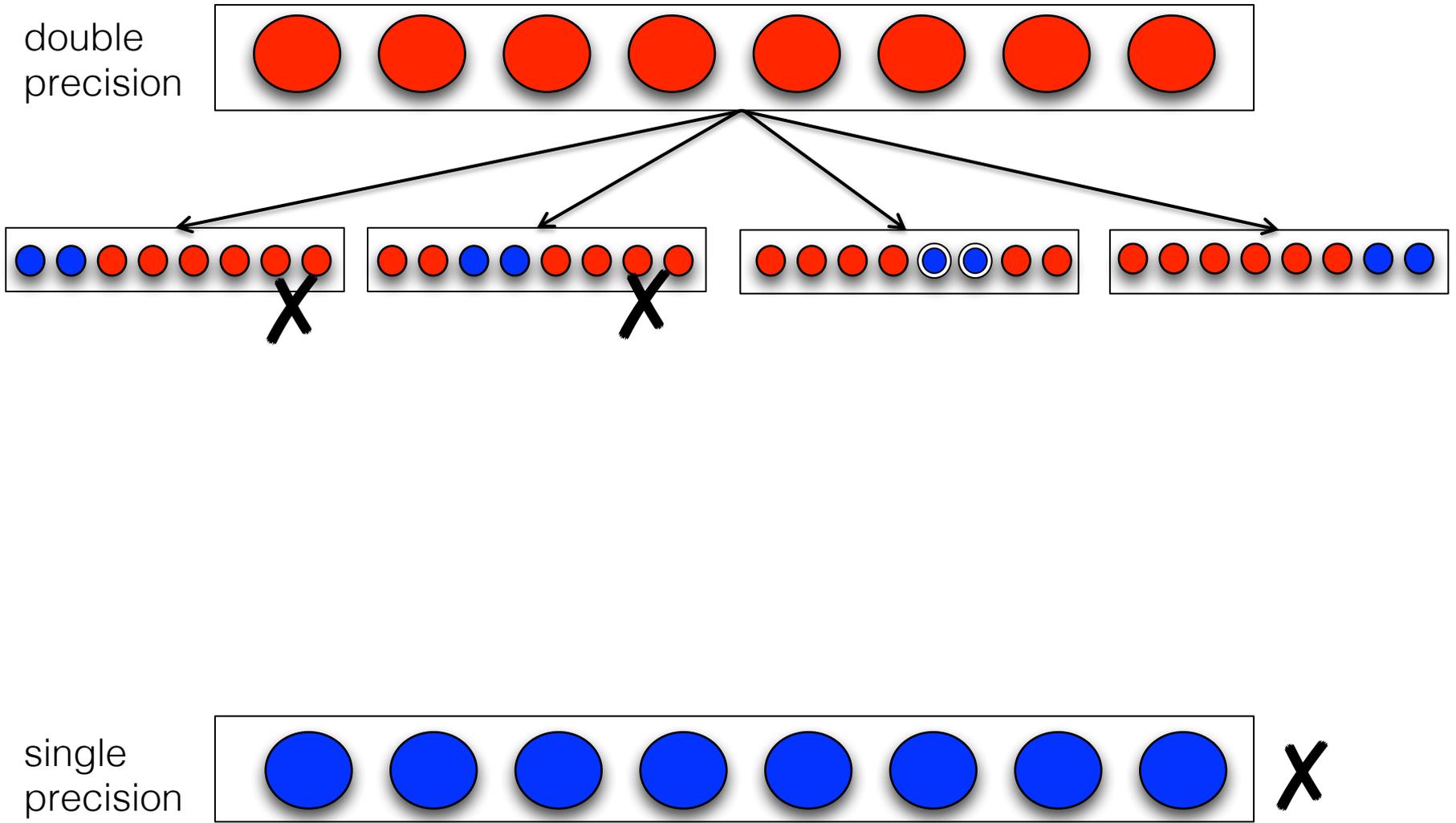
# Searching for Type Configuration



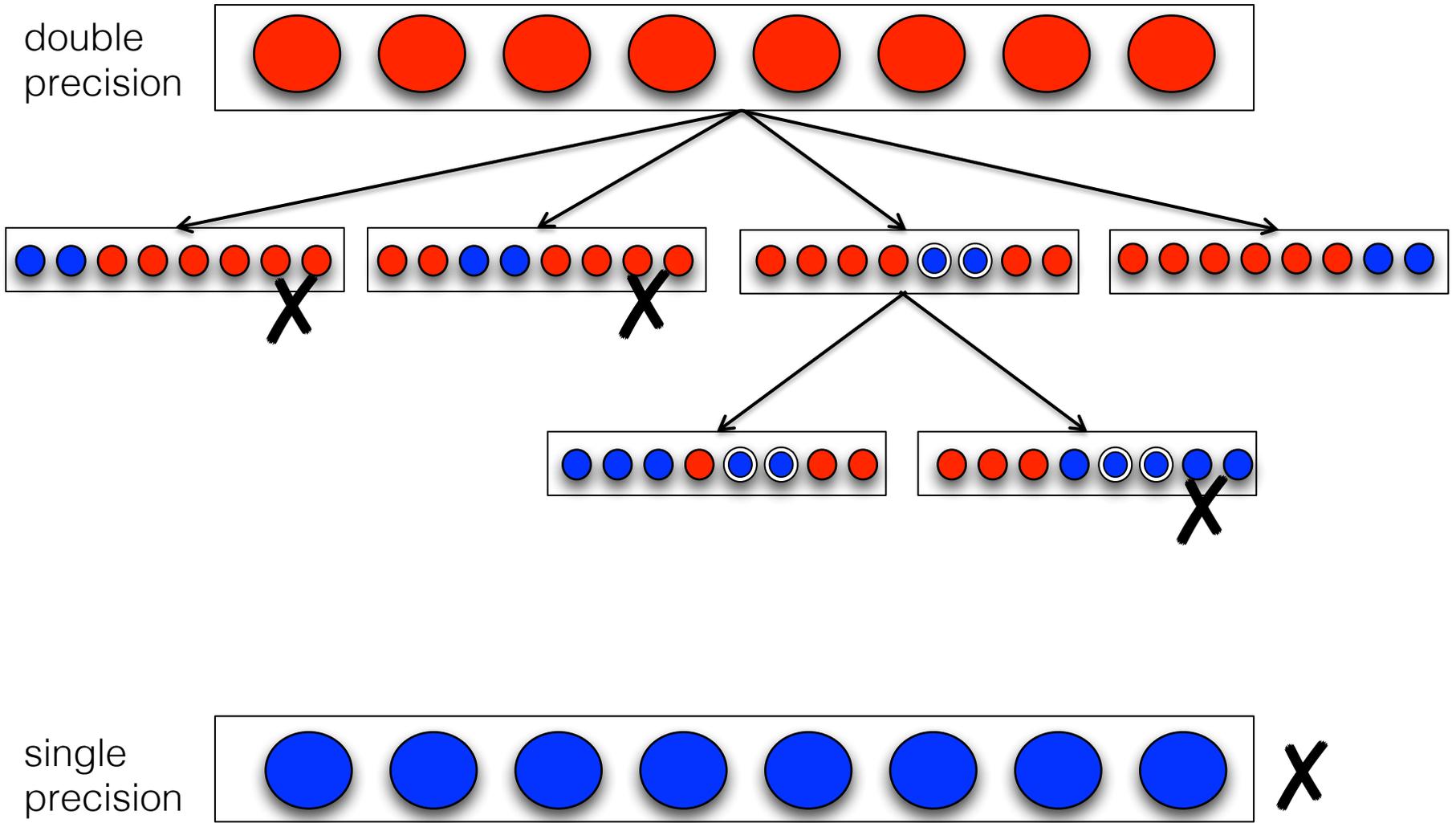
# Searching for Type Configuration



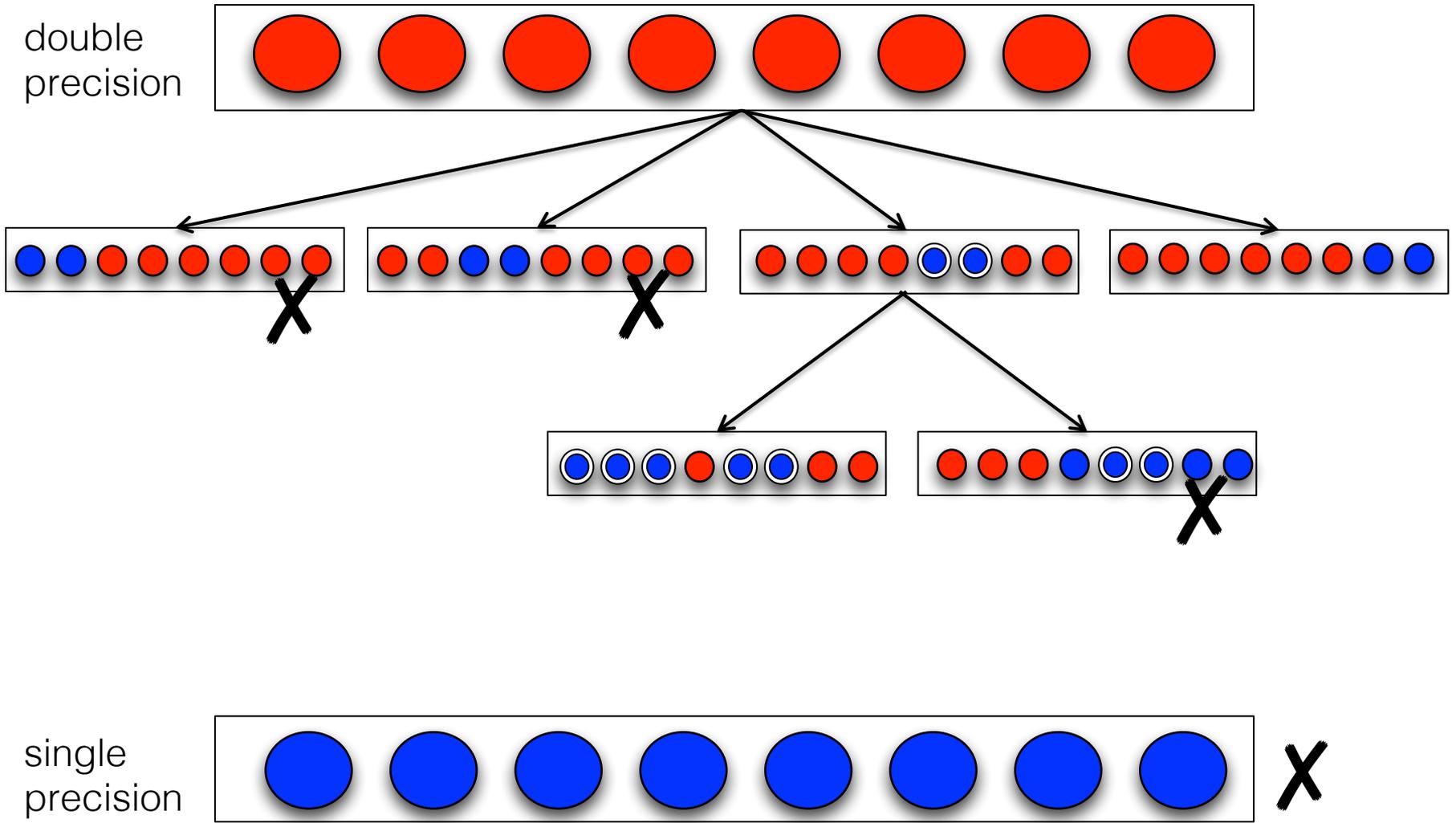
# Searching for Type Configuration



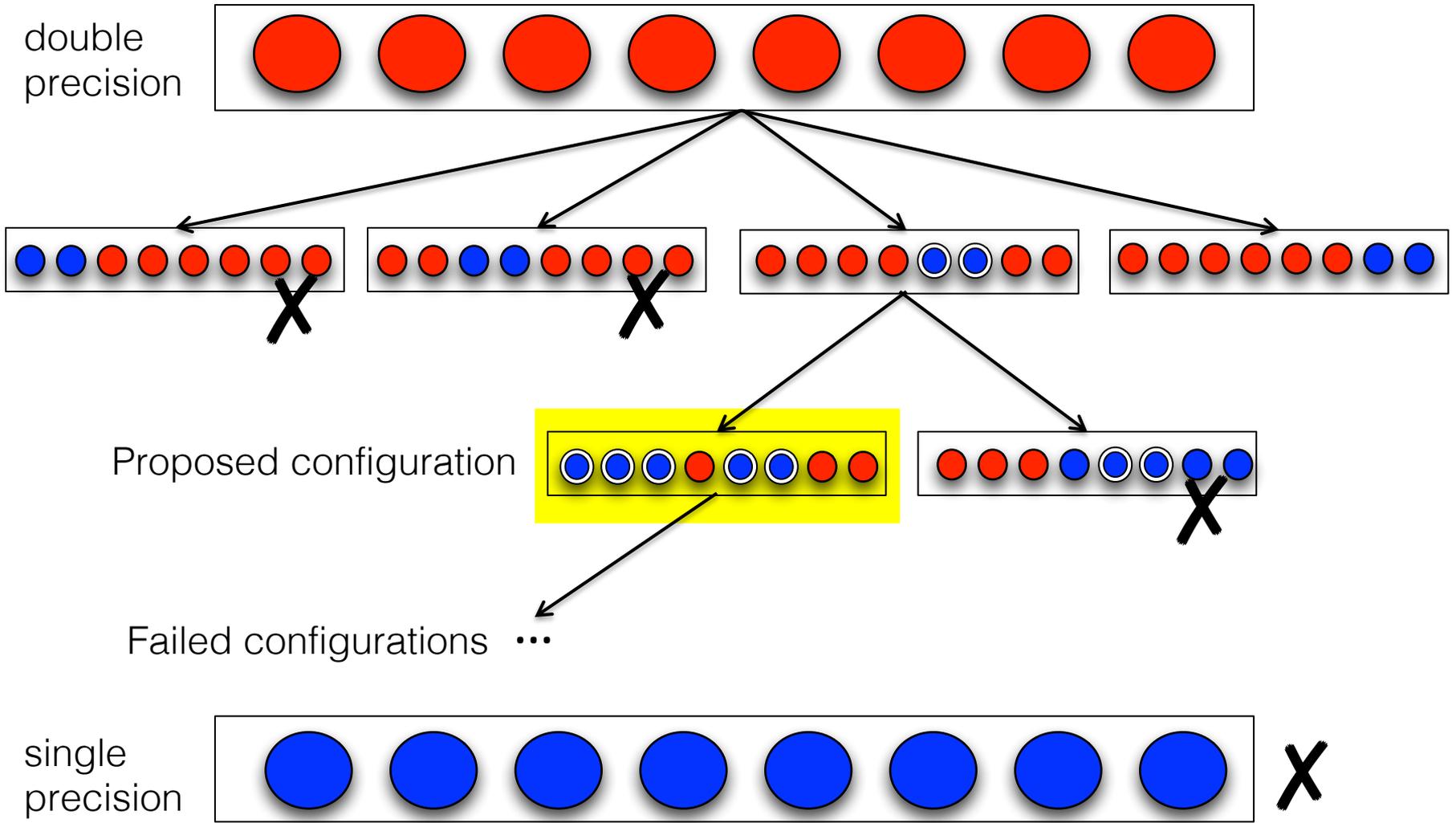
# Searching for Type Configuration



# Searching for Type Configuration



# Searching for Type Configuration



# Applying Type Configuration

- Automatically generate program variants
  - Reflect type configurations produced by the algorithm
- Intermediate representation
  - LLVM IR
- Transformation rules for each LLVM instruction
  - `alloca`, `load`, `store`, `fadd`, `fsub`, `fpext`, `fptrunc`, etc.
  - Changes equivalent to modifying the program at the source level
  - Clang plugin to provide modified source code
- Able to run resulting modified program
  - Evaluate type configuration: accuracy & performance

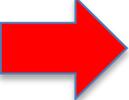
# Where to Find Precimonious

- Precimonious is open source
  - Most recent version can be found at <https://github.com/ucd-plse/precimonious>
- Dockerfile and examples
  - Tutorial on Floating-Point Analysis Tools at SC'19 and PEARC'19 <http://fpanalysistools.org>
  - Dockerfile and examples can be found at <https://github.com/ucd-plse/tutorial-precision-tuning>

# How to Use Precimonious

- Initial requirements
  - Does your program compile with clang?
  - Where does your program store the result?
  - How much error are you willing to tolerate?
    - Examples:  $10^{-4}$ ,  $10^{-6}$ ,  $10^{-8}$ , and  $10^{-10}$
  - Do you have representative inputs to use during tuning?
- Optional information
  - Are there specific functions/variables to focus on, or to ignore during tuning?
- What you get
  - Listing of variables (and function) and their proposed types
  - Useful start point to identify areas of interest

# Limitations and Recommendations

- Type configurations rely on program inputs tested
  - No guarantees if worse conditioned input
  - Use representative inputs whenever possible
  - Consider input generation tools, e.g., S3FP [1], FPGen [2], etc.
- Analysis scalability
  - Scalability limitations when tuning long-running applications
  -  – Need to reduce search space, and reduce number of runs
  - Consider starting with a specific area of the program
  - Consider synthesizing smaller workloads
- Analysis effectiveness
  -  – Black-box approach does not exploit relationship among variables

[1] W. Chiang, G. Gopalakrishnan, Z. Rakamaric and A. Solovyev. “Efficient Search for Inputs Causing High Floating-point Errors”, PPOPP 2014.

[2] H. Guo and C. Rubio-González. “Efficient Generation of Error-Inducing Floating-Point Inputs via Symbolic Execution”, ICSE 2020.

# Dynamic Tools for Precision Tuning

Precimonious

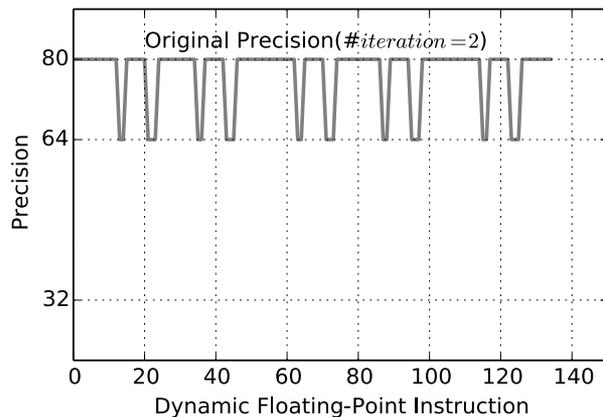
- Dynamic Analysis for Precision Tuning
  - Black-box approach to systematically search over variable types and functions

HiFPTuner

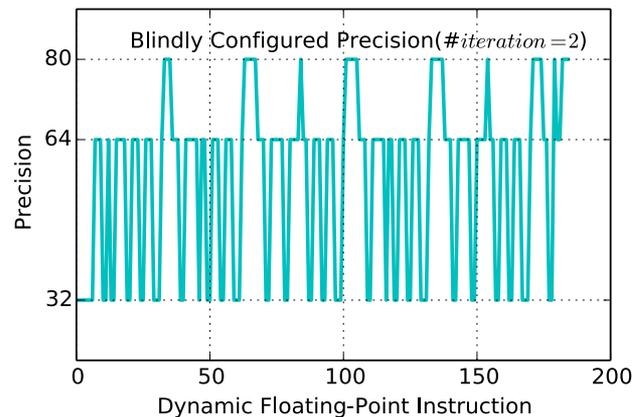
- Hierarchical Precision Tuner
  - Leverages relationship among variables to reduce search space and number of runs

# Impact of Precision Shifting

- Precimonious follows a black-box approach
  - Related variables assigned types independently
  - Large number of variables → Slow search
  - More type casts → Less speedup

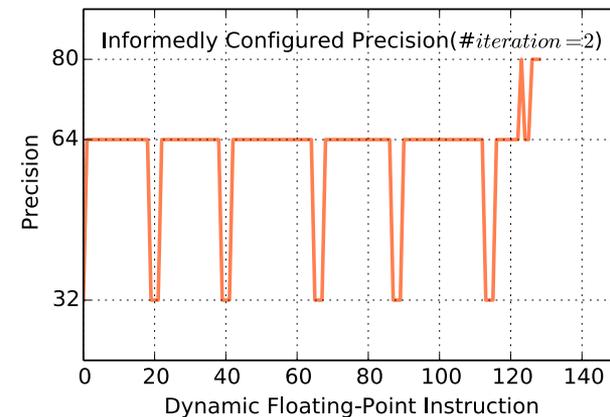


Original



Local minimum

Uses lower precision  
Speedup: 78.7%

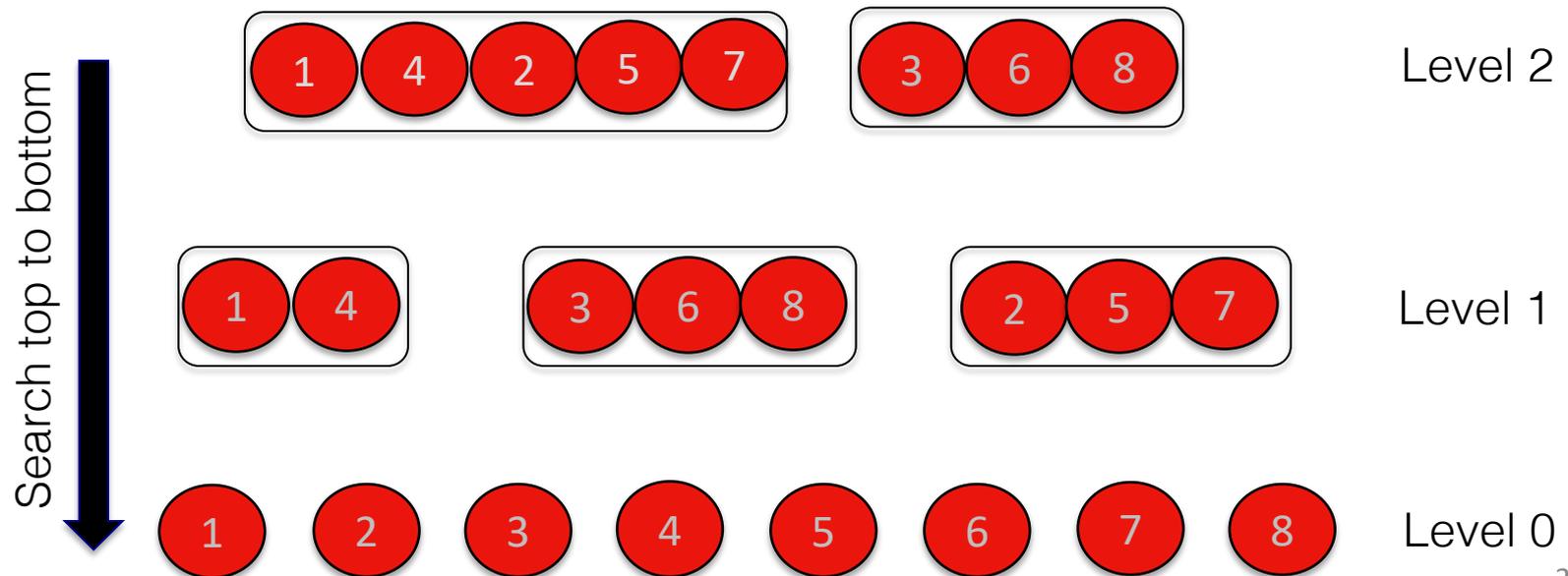


Global minimum

Shifts precision less often  
Speedup: 90%

# Exploiting Community Structure

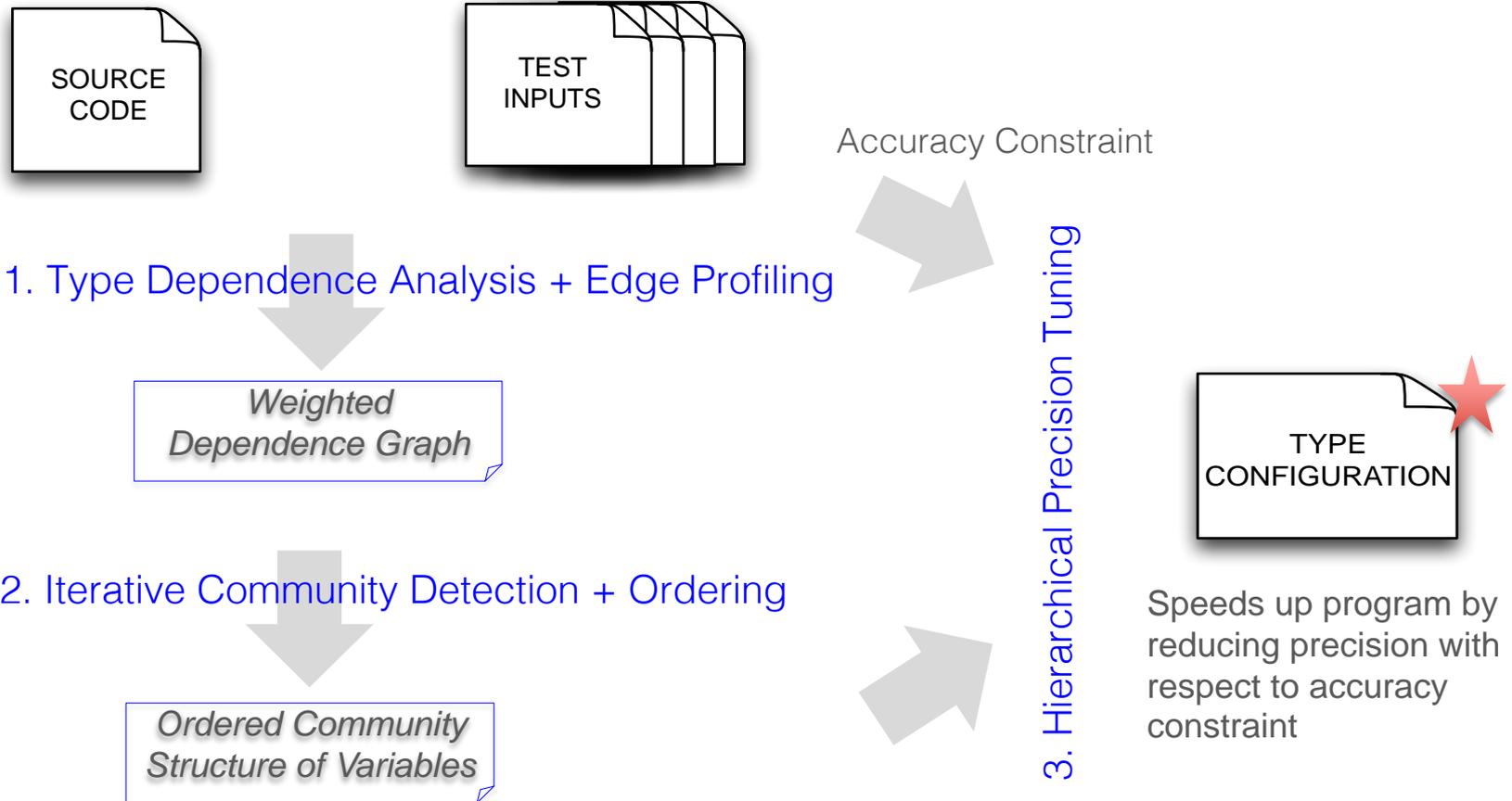
- Can we leverage the program to perform a more informed precision tuning?
- White box nature
  - Related variables pre-grouped into hierarchy → Same type
  - Fewer groups in search space → Faster search
  - Fewer type casts → Larger speedups



# HiFPTuner Approach

*Hierarchical Floating-Point Precision Tuning*

<https://github.com/ucd-plse/HiFPTuner>



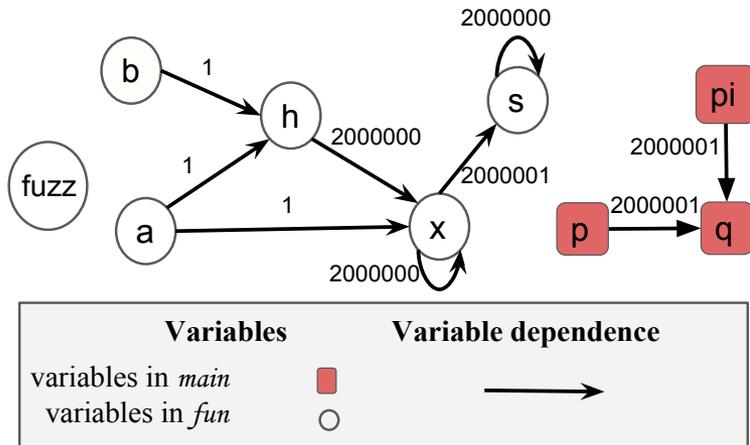
H. Guo and C. Rubio-González. "Exploiting Community Structure for Floating-Point Precision Tuning", ISSTA 2018.

M. Girvan and M.E. Newman. "Community Structure in Social and Biological Networks", NAS 2002.

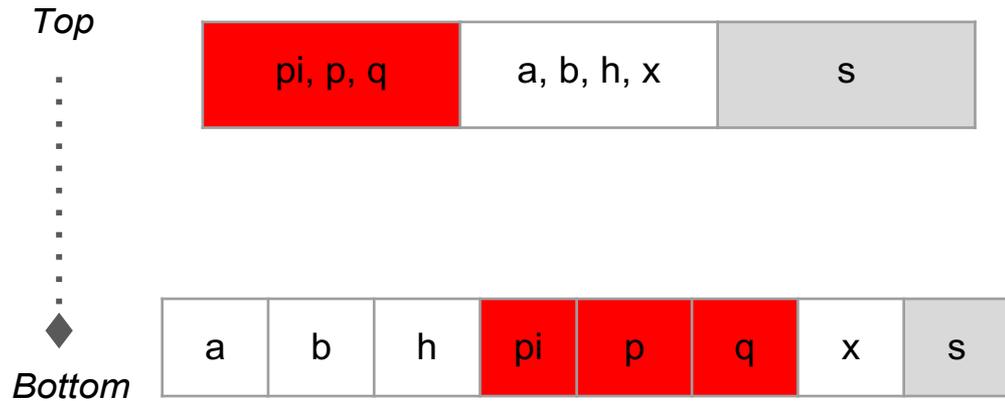
F. Radicchi, C. Castellano, F. Cecconi, V. Loreto, and D. Parisi. "Defining and Identifying Communities in Networks", NAS 2004.

# Simpsons Example

Weighted dependence graph



Ordered community structure



Found global minimum configuration that leads to 90% speedup!

HiFPTuner explores 24 configurations, almost 5x fewer configurations

# Better Scalability & Speedup

- Items at top level of hierarchy reduced by 53% on average in comparison to Precimonious
- Higher search efficiency over Precimonious for 75% of the programs in our study
  - Explored 45% fewer configurations
- HiFPTuner finds better configurations for half of the programs, with up to 90% speedup

# Where to Find HiFPTuner

- HiFPTuner is open source
  - <https://github.com/ucd-plse/HiFPTuner>
- Dockerfile and examples
  - Tutorial on Floating-Point Analysis Tools at SC'19 and PEARC'19  
<http://fpanalysistools.org>
  - Dockerfile and examples can be found at  
<https://github.com/ucd-plse/tutorial-precision-tuning>
- Same requirements as Precimonious

# Comparison of Precision Tuners

	PROS	CONS
Precimonious	<ul style="list-style-type: none"> <li>+ Considers both accuracy and performance</li> <li>+ Works for medium size non-trivial programs</li> <li>+ Easily configurable</li> </ul>	<ul style="list-style-type: none"> <li>- Requires a run for each type configurations</li> <li>- Ordering of variables may give different results</li> </ul>
HiFPTuner	<ul style="list-style-type: none"> <li>+ White-box <i>hierarchical</i> approach, groups variables based on their usage</li> <li>+ Over twice as fast as Precimonious</li> <li>+ Finds configurations that lead to higher speedups</li> </ul>	<ul style="list-style-type: none"> <li>- Requires program profiling</li> <li>- Still requires a run for each type configuration</li> </ul>
Blame Analysis [1]	<ul style="list-style-type: none"> <li>+ Performs shadow execution, requires a single run of the program</li> <li>+ Identifies variables that can be single precision</li> <li>+ Combined with Precimonious leads to 9x faster analysis</li> </ul>	<ul style="list-style-type: none"> <li>- Focuses on accuracy, not performance</li> <li>- 50x overhead by shadow execution engine</li> <li>- Still black box approach</li> </ul>

[1] C. Rubio-González, C. Nguyen, B. Mehne, K. Sen, J. Demmel, W. Kahan, C. Iancu, W. Lavrijsen, D.H. Bailey and D. Hough. "Floating-Point Precision Tuning Using Blame Analysis", ICSE 2016.

# Current Challenges for HPC Applications

1. Type configurations rely on program inputs tested
  - How problematic is this for HPC applications?
  - Can we leverage application-dependent correctness metrics?
2. Analysis scalability
  - How can we further reduce the search space?
  - How can we reduce the number of program runs?
3. Analysis effectiveness
  - How far are we from the best configuration(s)?
  - Are there other program transformations to explore?
  - Can we incorporate domain knowledge to guide search?
4. Benchmarks
  - Difficult to find programs to test precision tuners at scale
  - Need for collaboration between application and tool developers

# Some Useful Resources

- Other recent precision tuners

I. Laguna, P.C. Wood, R. Singh and S. Bagchi. “GPUMixer: Performance-Driven Floating-Point Tuning for GPU Scientific Applications”, ISC 2019.

M. Lam, T. Vanderbruggen, H. Menon and M. Schordan. “Tool Integration for Source-Level Mixed Precision”. CORRECTNESS@SC 2019.

S. Cherubin, D. Cattaneo, M. Chiari and G. Agosta. “Dynamic Precision Autotuning with TAFFO”. ACM Trans. Archit. Code Optim. 2019.

P.V. Kotipalli, R. Singh, P. Wood, I. Laguna and S. Bagchi. “AMPT-GA: Automatic Mixed Precision Floating Point Tuning for GPU Applications”. ICS 2019.

H. Menon, M. Lam, D. Osei-Kuffuor, M. Schordan, S. Lloyd, K. Mohror and J. Hittinger. “ADAPT: Algorithmic Differentiation Applied to Floating-Point Precision Tuning”, SC 2018.

E. Darulova, E. Horn and S. Sharma. “Sound Mixed-Precision Optimization with Rewriting”. ICCPS 2018.

W. Chiang, M. Baranowski, I. Briggs, A. Solovyev, G. Gopalakrishnan and Z. Rakamaric. “Rigorous Floating-Point Mixed-Precision Tuning”. POPL 2017.

- Check out recent survey on reduced precision

S. Cherubin and G. Agosta. “Tools for Reduced Precision Computation: A Survey. ACM Computing Surveys 2020.

- An exhaustive list of tools: <https://fpbench.org/community.html>

# SC Workshop on Software Correctness

A promotional banner for the Fourth International Workshop on Software Correctness for HPC Applications (SC20). The banner features a dark purple background on the left and a circular inset on the right showing a close-up of a computer circuit board. The text is white and orange. The URL is in white. The logos for SC20 and TCHPC are at the bottom.

Fourth International Workshop on  
**Software Correctness**  
for HPC Applications

<https://correctness-workshop.github.io/2020/>

 **SC20**  
Atlanta, GA | more than hpc.

In cooperation with  
 **TCHPC**

Co-Organized with Ignacio Laguna from Lawrence Livermore National Lab  
November 11<sup>th</sup>, 2020 (half day, 2:30pm to 6:30pm EDT)

# Summary

- Precision tuning can have an important impact on the performance of HPC applications
- Many techniques for precision tuning
  - Different approaches: dynamic vs. static
- We discussed two of our tools for precision tuning
  - Precimonious and HiFPTuner
- A lot of progress, but there are still challenges and opportunities to apply precision tuning at scale
- **Application and tool developers** must work together to improve scalability and effectiveness of precision tuning

# Collaborators

## UC Berkeley



Cuong  
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Diep  
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Ben  
Mehne



James  
Demmel



William  
Kahan



Koushik  
Sen

## UC Davis



Hui  
Guo



David  
Bailey

## LBNL



Costin  
Iancu



Wim  
Lavrijsen

## Oracle



David  
Hough

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