Center for Scalable Application Development Software

Sampling-based Strategies for Measurement and Analysis

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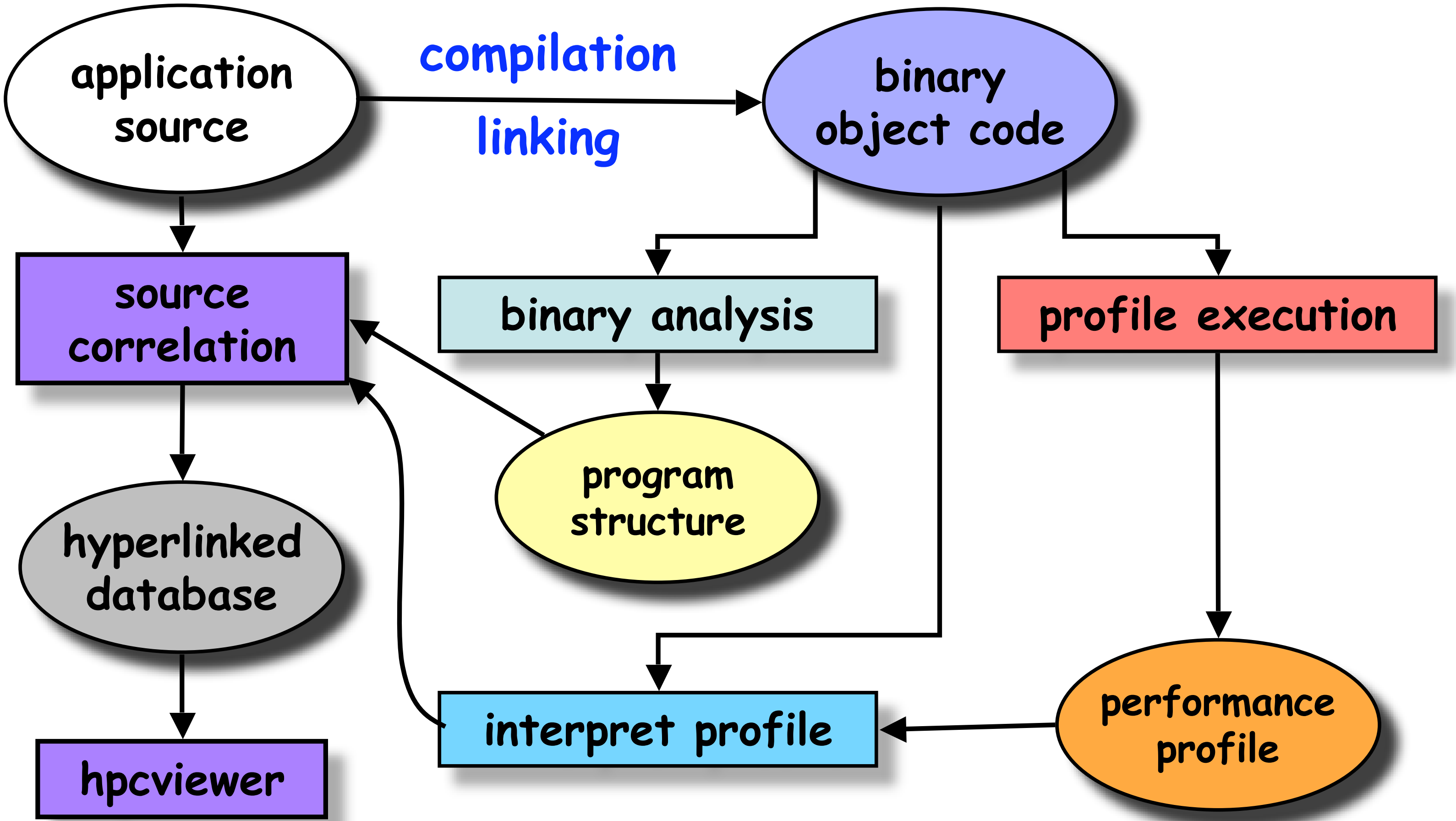
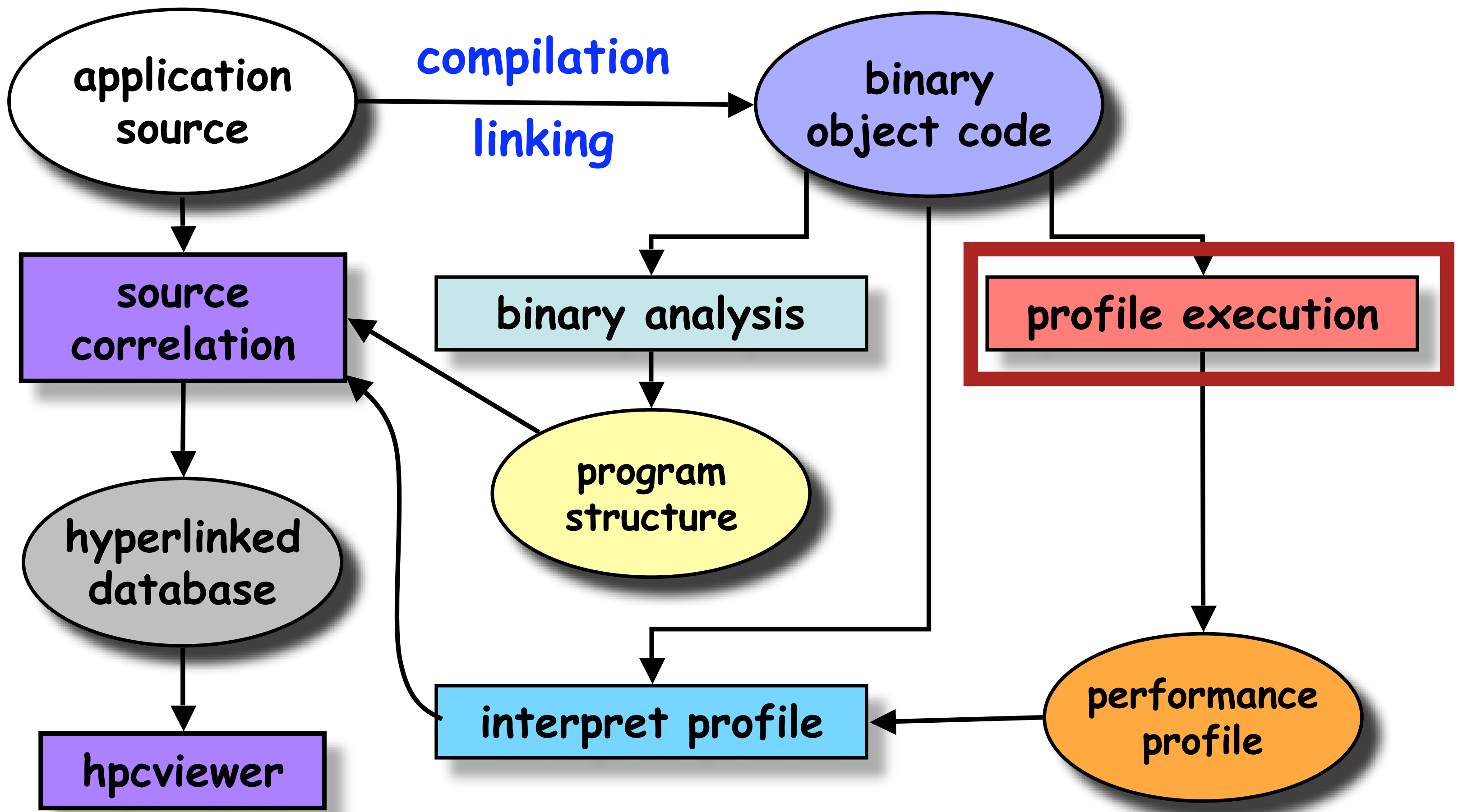
Rice’s HPCToolkit Philosophy

- Work at binary level for language independence
  - support multi-lingual codes with external binary-only libraries
- Profile rather than adding code instrumentation
  - minimize measurement overhead and distortion
  - enable data collection for large-scale parallelism
- Collect and correlate multiple performance measures
  - can’t diagnose a problem with only one species of event
- Compute derived metrics to aid analysis
- Support top down performance analysis
  - intuitive enough for scientists and engineers to use
  - detailed enough to meet the needs of compiler writers
- Aggregate events for loops and procedures
  - accurate despite approximate event attribution from counters
  - loop-level info is more important than line-level info

HPCToolkit Workflow

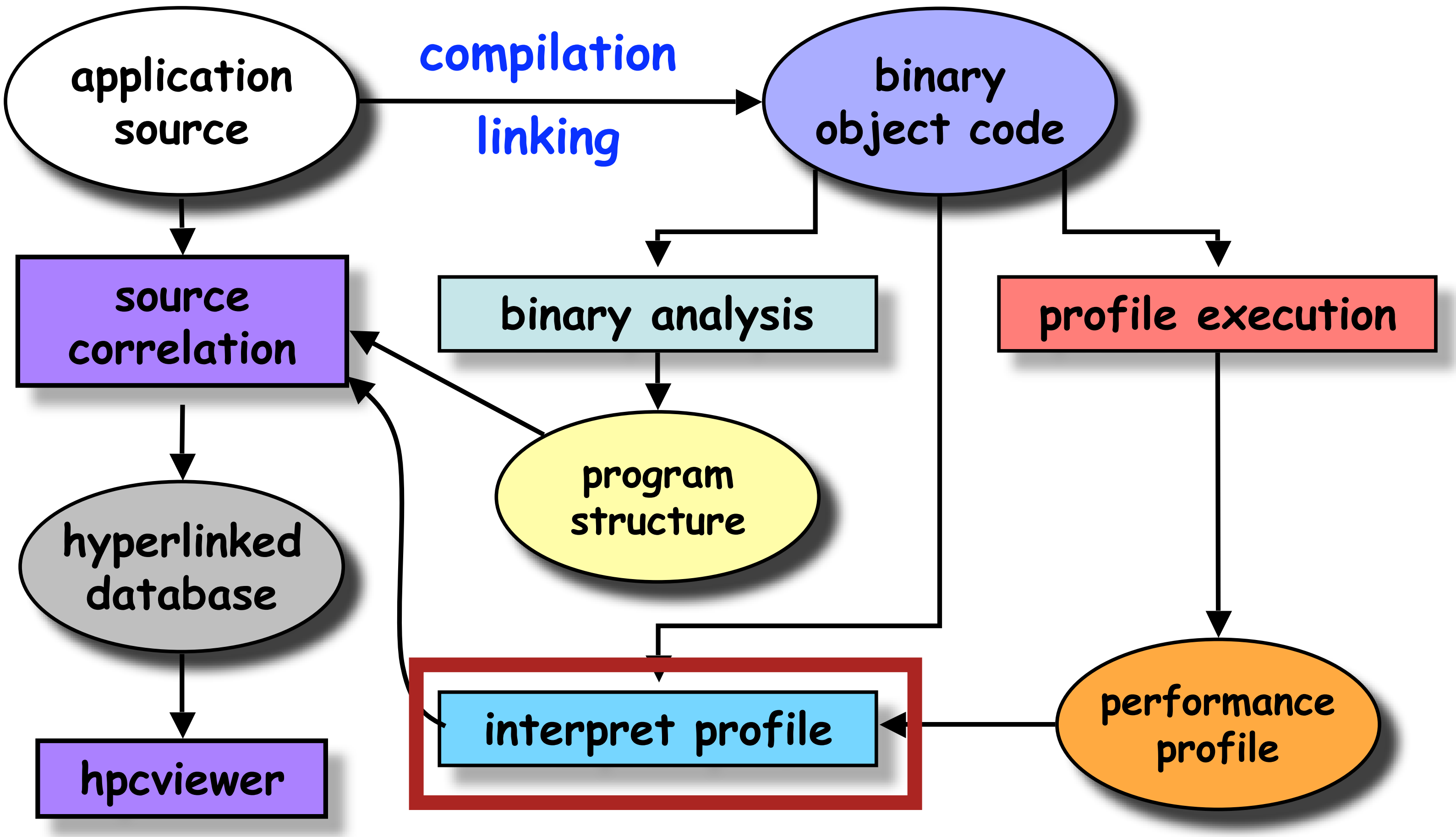


HPCToolkit Workflow



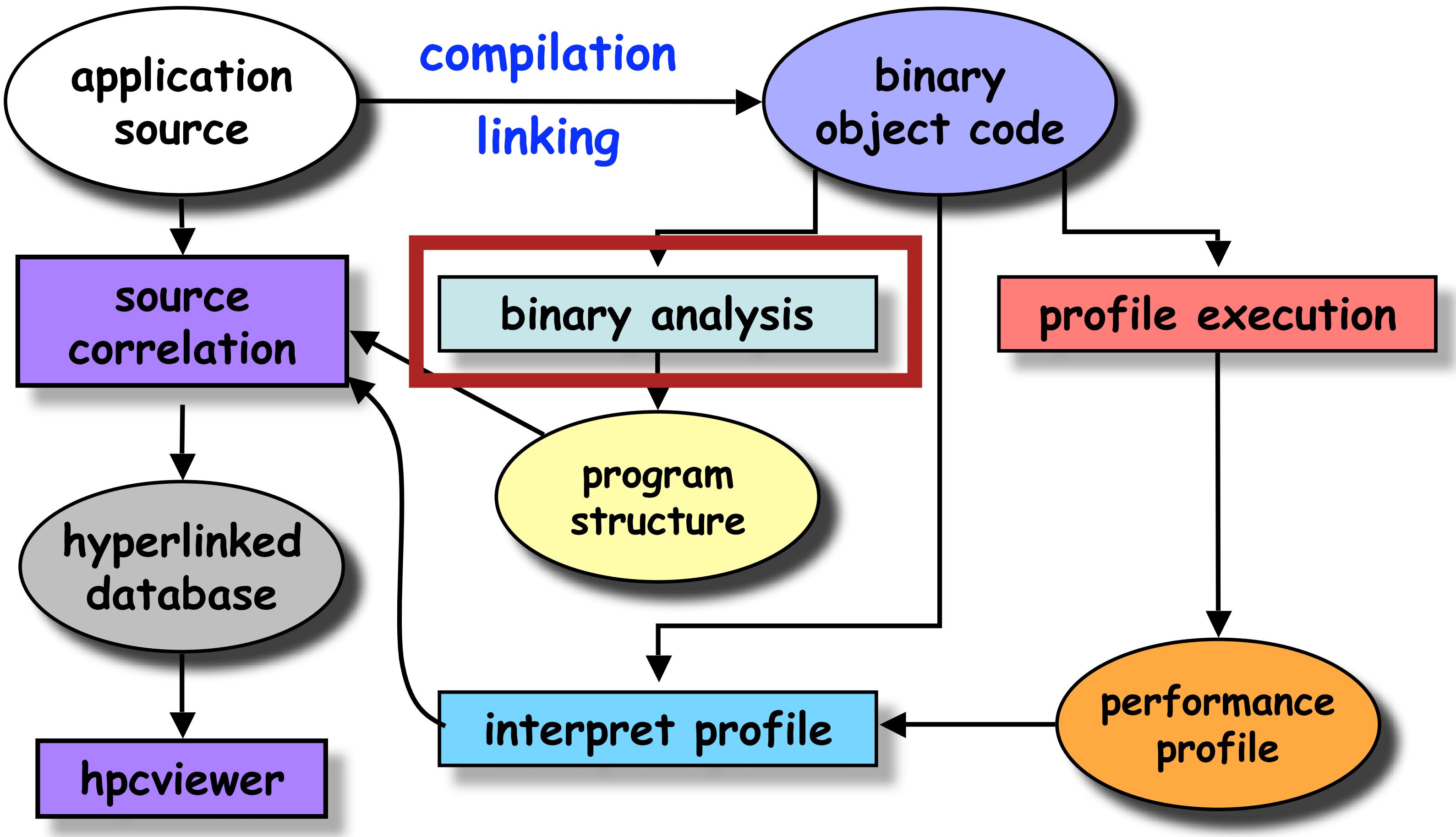
– launch optimized application binaries
– collect statistical profiles of events of interest

HPCToolkit Workflow



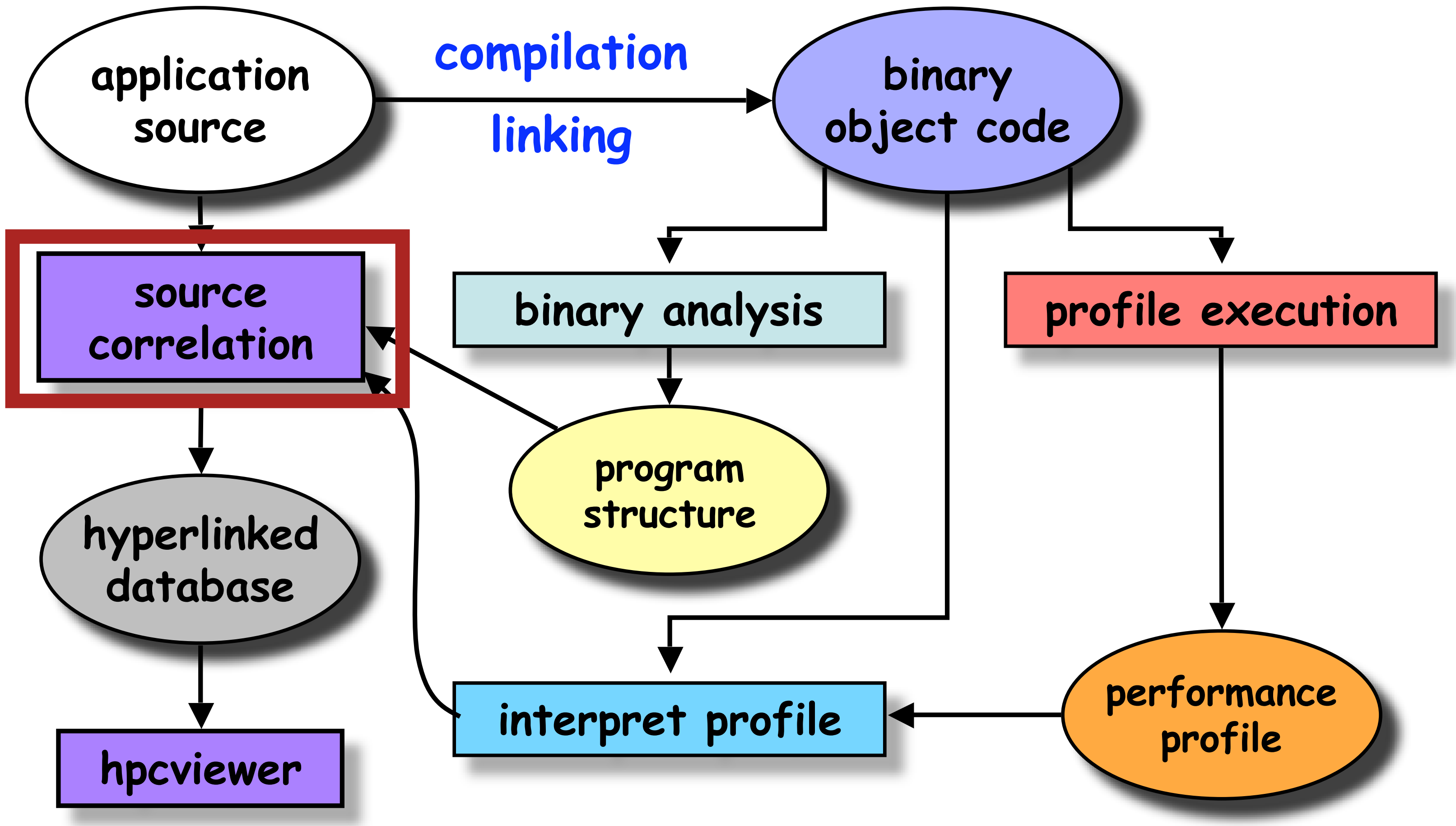
– decode instructions and combine with profile data

HPCToolkit Workflow



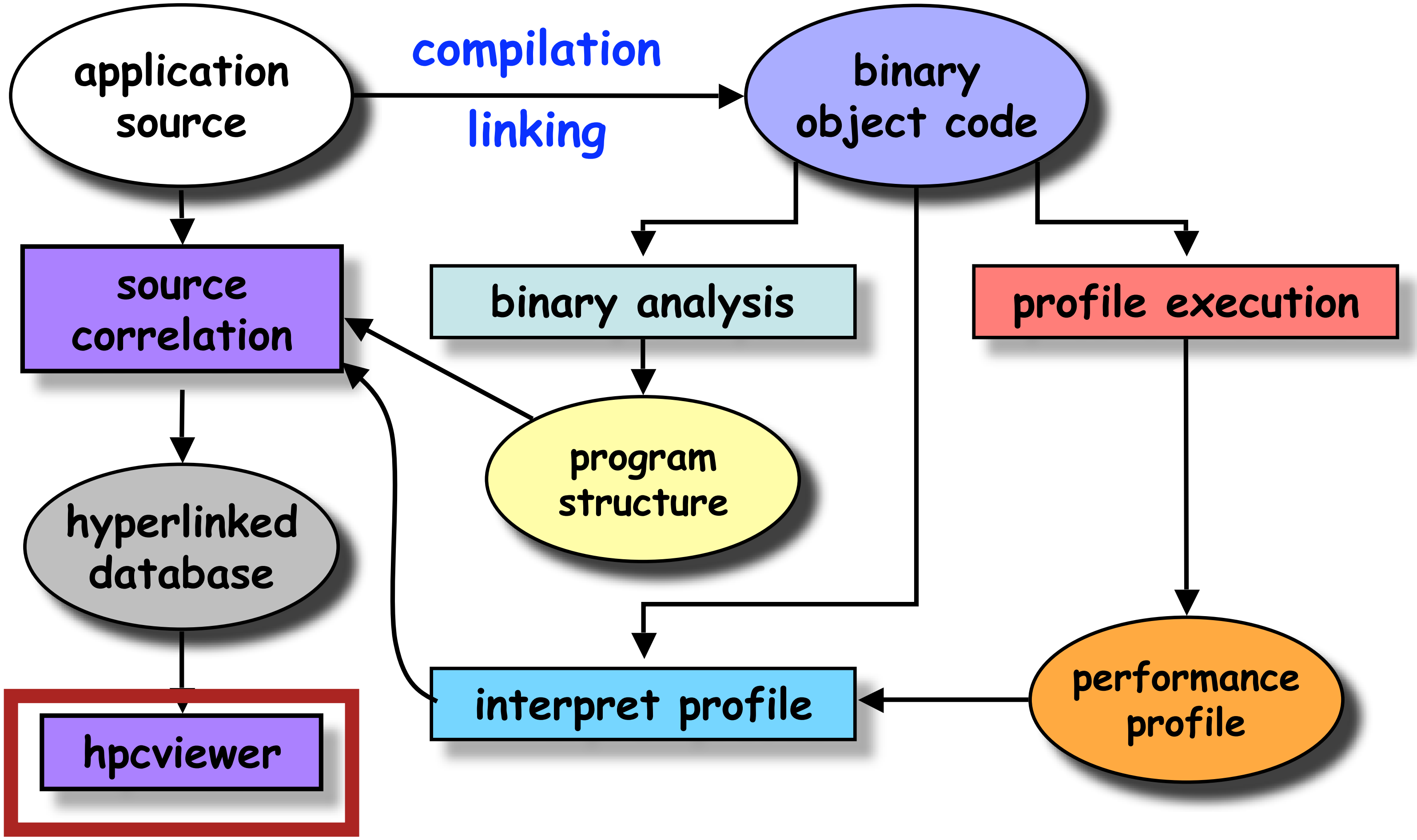
– extract loop nesting & inlining from executables

HPCToolkit Workflow



- synthesize new metrics as functions of existing metrics
- relate metrics and structure to program source

HPCToolkit Workflow

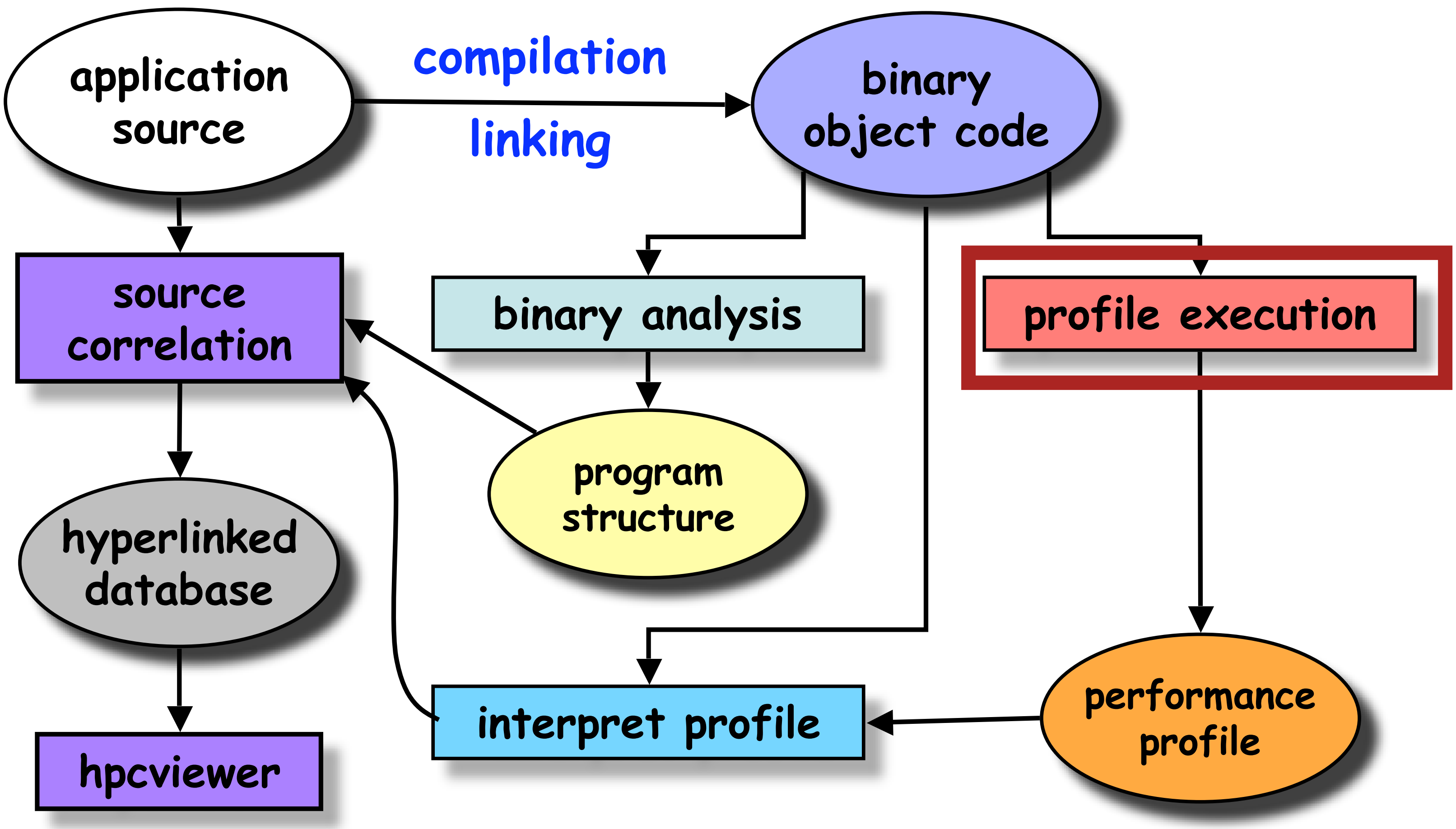


- support top-down analysis with interactive viewer
- analyze results anytime, anywhere

Outline

- Sampling based measurement
- Binary analysis
- User interface
- Scalability analysis
- Components
  - ours
  - our desires
- Related modeling activities

HPCToolkit Workflow



Measurement Challenges

Performance often depends upon context

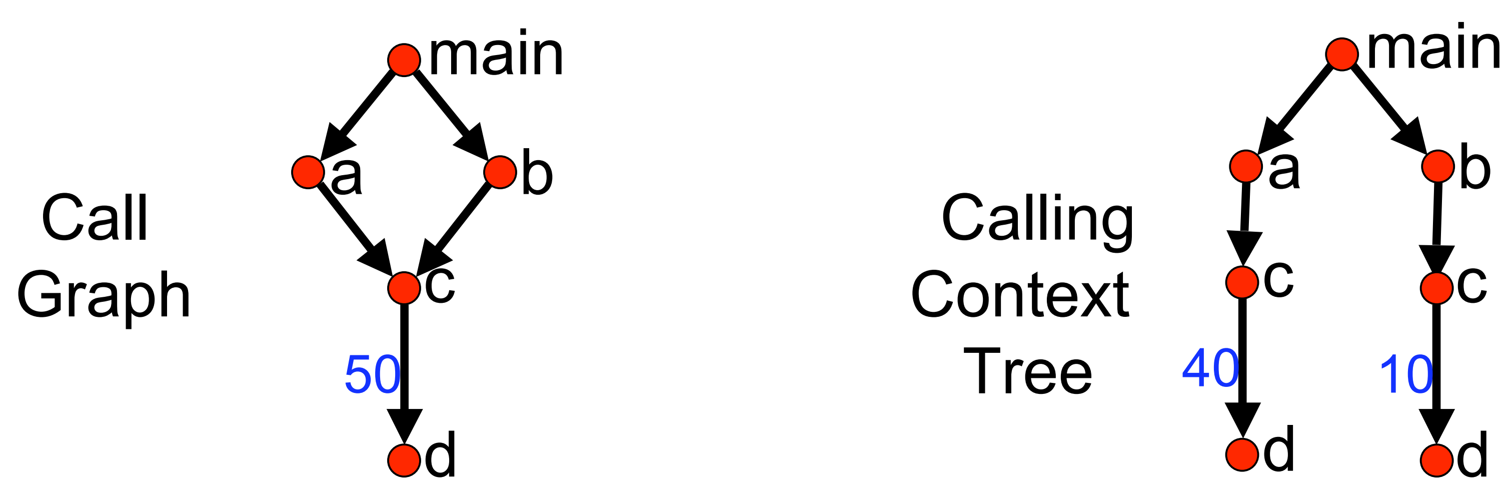
- Layered design
  - math libraries
  - communication libraries in parallel programs
- Generic programming, e.g. C++ templates
  - both data structures and algorithms

- Goals
  - identify and quantify context-sensitive behavior
  - differentiate between types of performance problems
    - cheap procedure called many times
    - expensive procedure called few times

Understanding Costs In Context

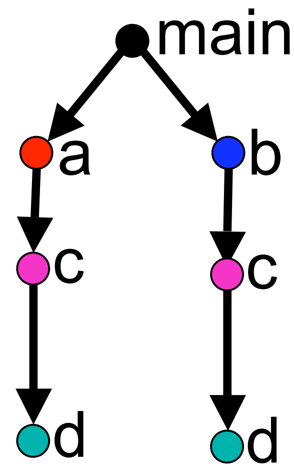
Call Path Profiling

- Measure time spent in each procedure
- Attribute time upward along call chain
- Report average time per call per calling context



A Torture Test

```
#define HUGE (1<<28)

void d() {}

void c(long n) {
  for(int j=0; j<HUGE/n; j++) d();
}

void a(void (*f)(long)) { f(1); f(1); }

void b(void (*f)(long)) { f(2); f(2); f(2); f(2); }

void main() { a(c); b(c); }
```



Results with Existing Tools

(for the torture test)

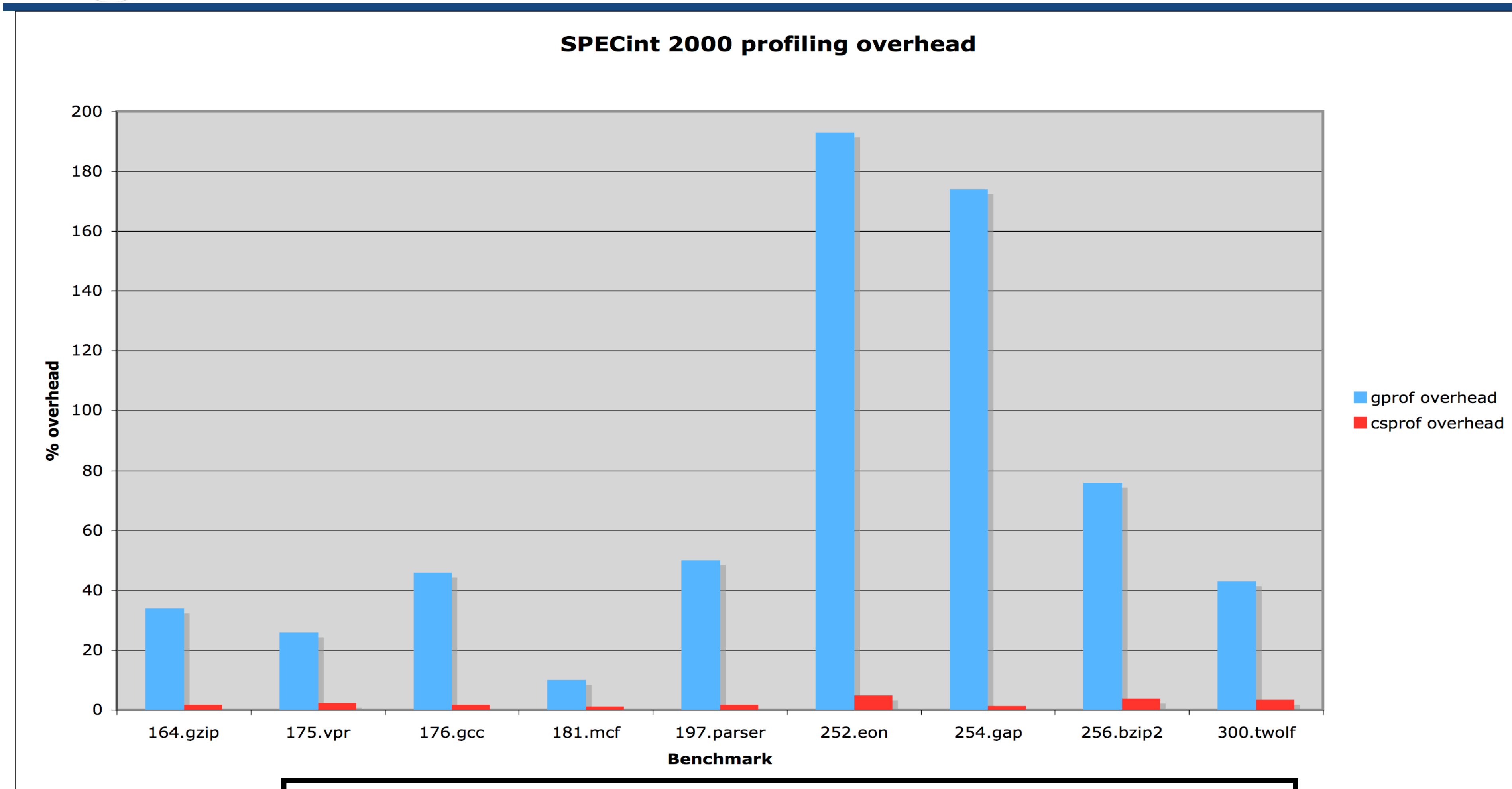
- Instrumentation-based profilers
  - gprof: dilates execution by a factor of 3-14
    - cannot distinguish different costs for calling contexts
  - Vtune: dilates execution by a factor of 31 (Linux+P4)!
- Call stack sampling profilers
  - e.g., Apple’s Shark, HP’s scgprof
    - can’t distinguish different costs for calling contexts

csprof: 1.5% overhead; accurate context-based attribution

Call Path Profiling Overview

- At each sample event
  - use call stack unwinding to identify full context
    - [vector of return addresses; PC]
  - record sample in a calling context tree (CCT)
    - captures common context between samples
  - “mark the current procedure frame”
    - replace frame’s return address with address of a “trampoline”
  - remember CCT path to marked frame
- When returning from a marked procedure frame
  - increment edge count of the last call edge in the memoized path
  - pop the last edge in the memoized path
  - mark the caller’s frame with the trampoline
  - return control to caller
- Low-overhead unwinding: need not unwind beyond marked frame

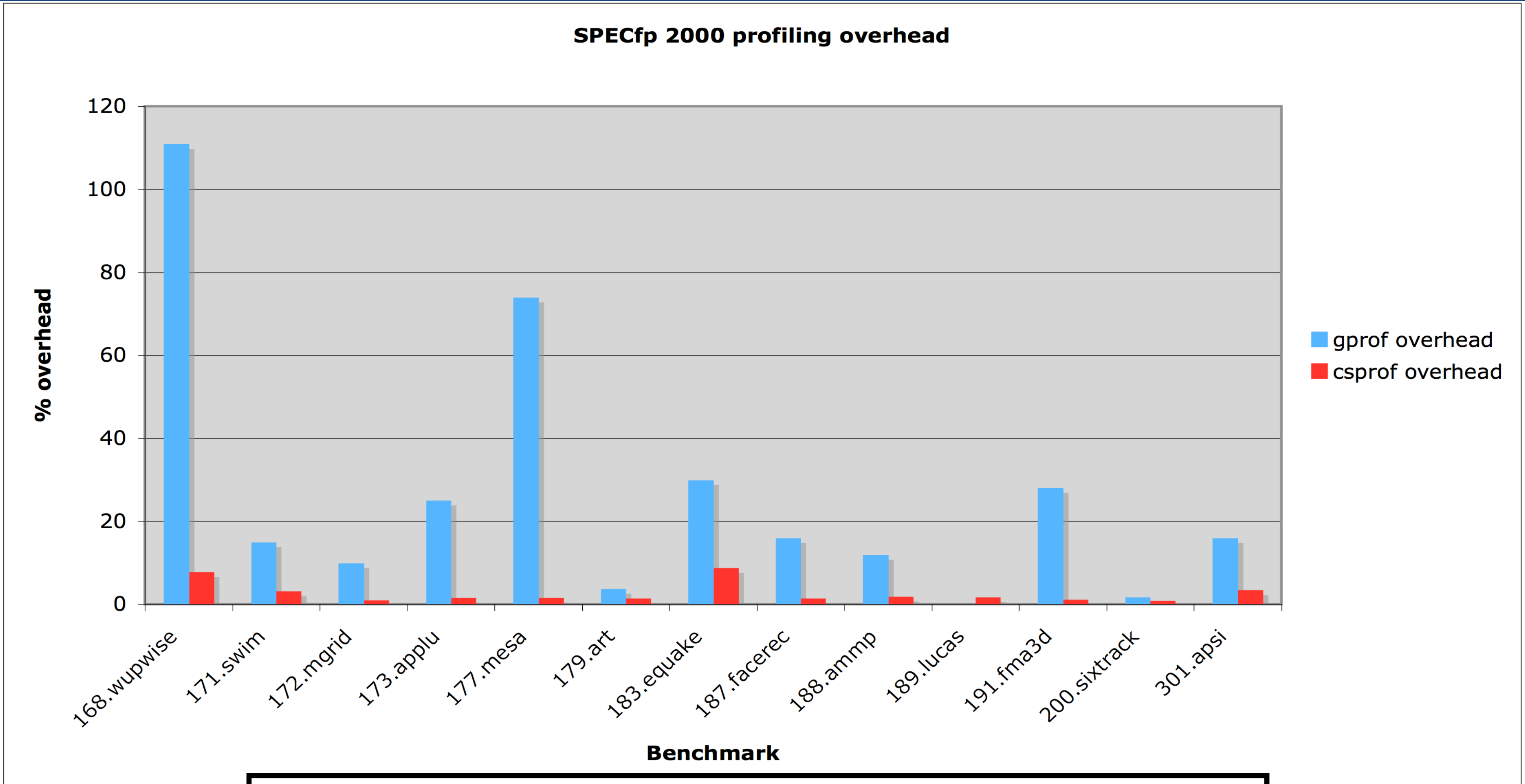
SPECint 2000 Benchmarks



Average overhead: gprof 82%, csprof 2.7%

(Opteron, gcc 4.1)

SPECfp 2000 Benchmarks



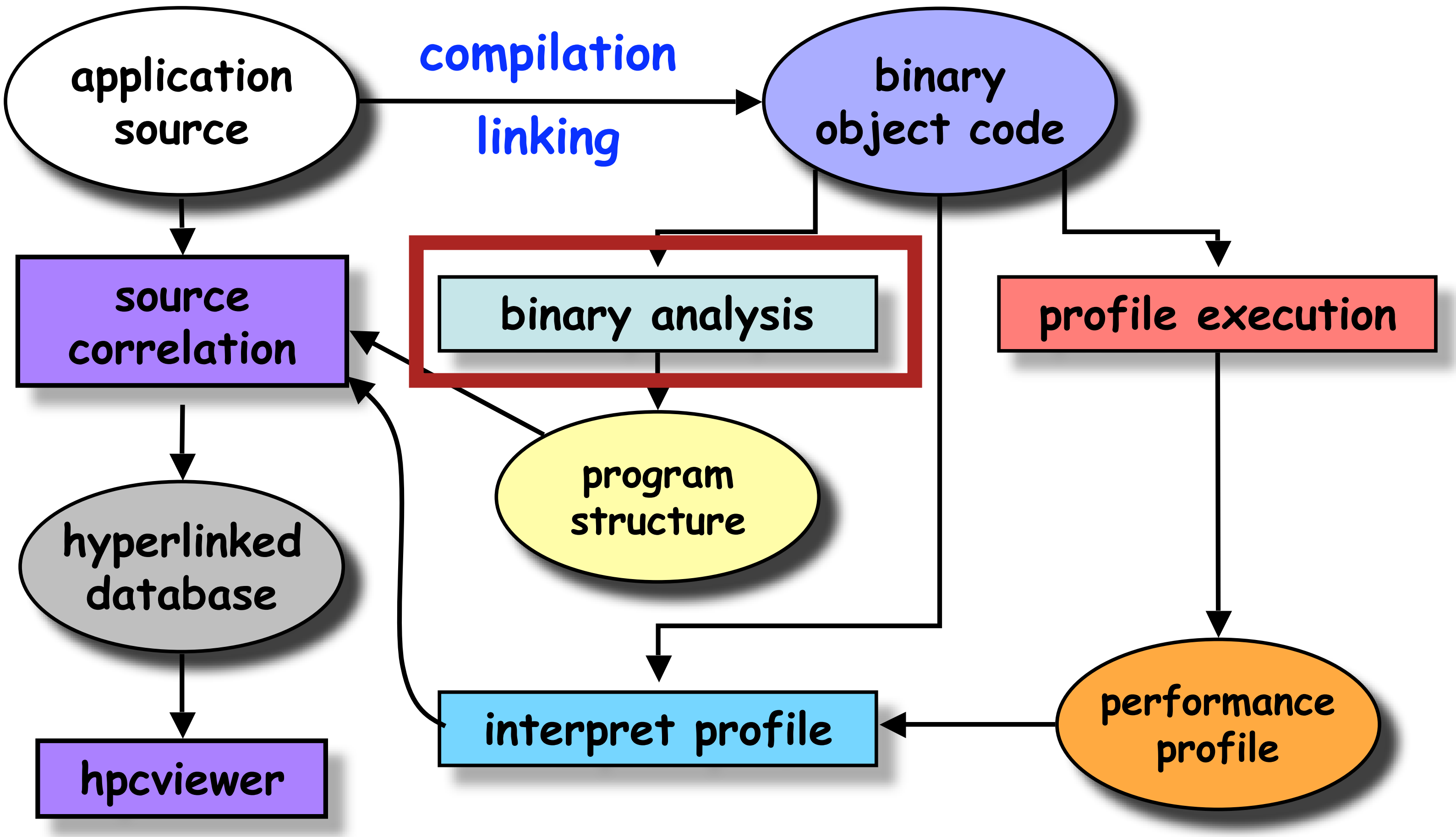
Average overhead: gprof 31%, csprof 3.2%

(Opteron, gcc 4.1)

Ongoing Call Path Profiler Refactoring

- Platform: OS, architecture
- Profiling flavor
  - flat vs. calling context (CC)
    - CC: precise vs. summary
    - CC: naive vs. smart unwinding (SU)
      - SU: compiler information vs. binary analysis (BA) vs. emulation
        - BA: eager vs. lazy
      - SU: edge counting vs. pure call stack sampling
  - threaded vs. non-threaded
- Initiation: preloading vs. static vs. attaching
- Synchronous vs. asynchronous events
- Asynchronous sample sources
  - timers, counters
  - instruction-based sampling
- Online control API

HPCToolkit Workflow



Why Binary Analysis?

- Understanding a program's performance requires understanding its structure
- Program structure after optimization may only vaguely resemble the program source
  - complex patterns of code composition
    - e.g. C++ expression templates
  - understanding loops is important to for understanding performance
    - account for significant time in data-intensive scientific codes
    - undergo significant compiler transformations

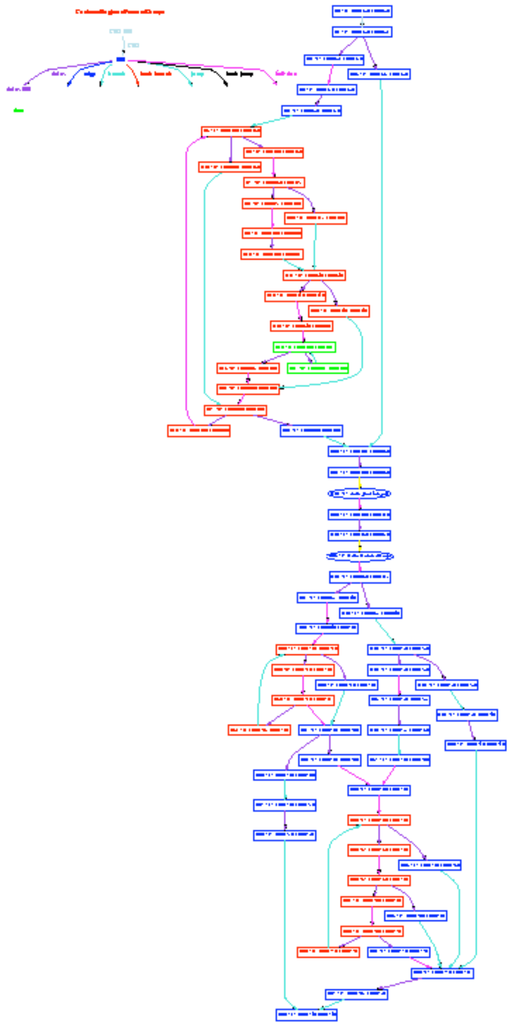
Goal: understand transformed <u>loops</u> in the context of transformed <u>routines</u>

Program Structure Recovery with `bloop`

Analyze an application binary

- Construct control flow graph from branches
- Identify natural loop nests using interval analysis
- Map instructions to source lines, procedures
  - leverage line map + DWARF debugging information
- Recover procedure boundaries
- Identify inlined code & its nesting in procedures and loops
- Normalize loop structure information to recover source-level view

Sample Flowgraph from an Executable



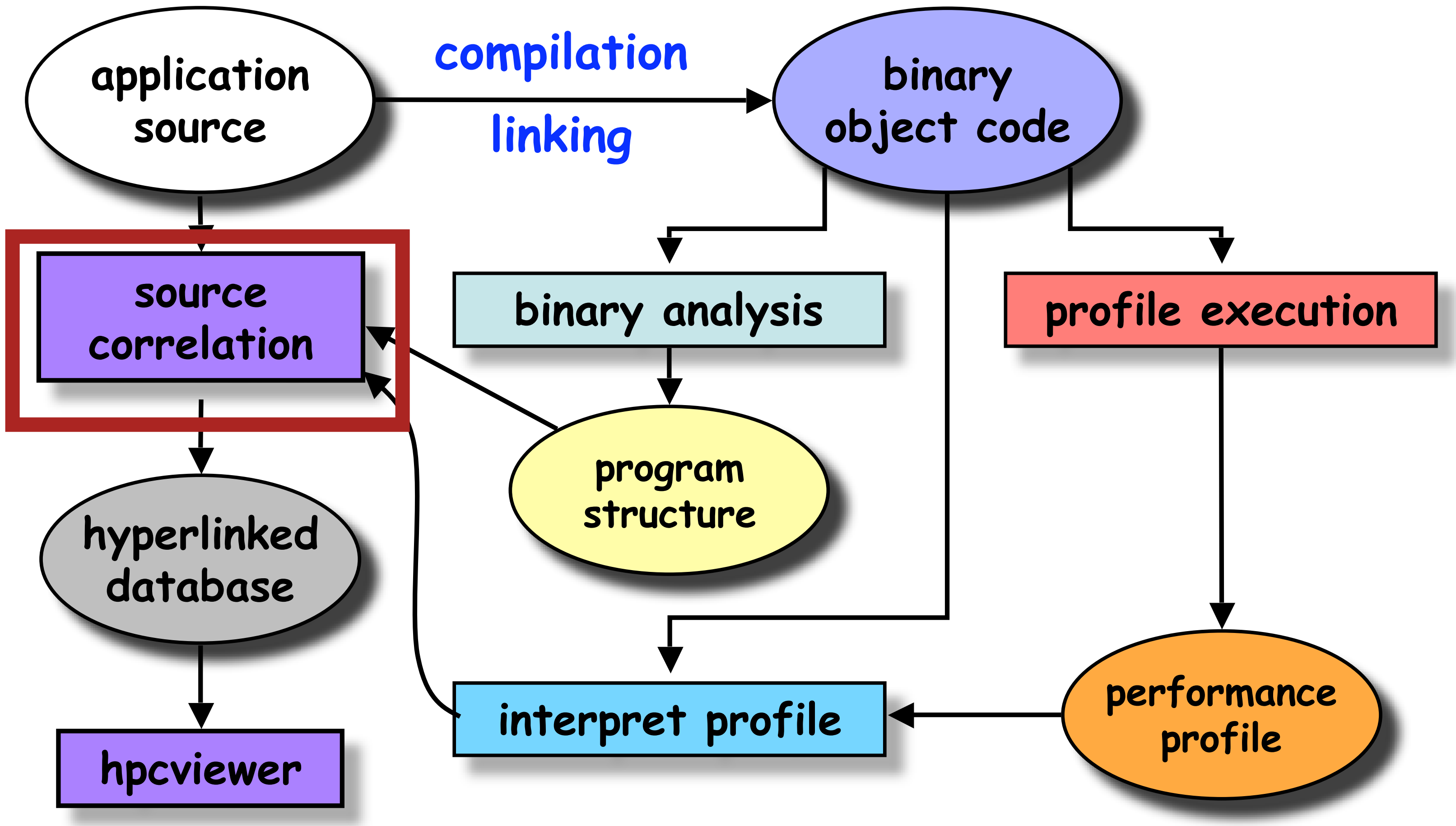
Loop nesting structure

- blue: outermost level
- red: loop level 1
- green loop level 2

Observation

optimization complicates program structure!

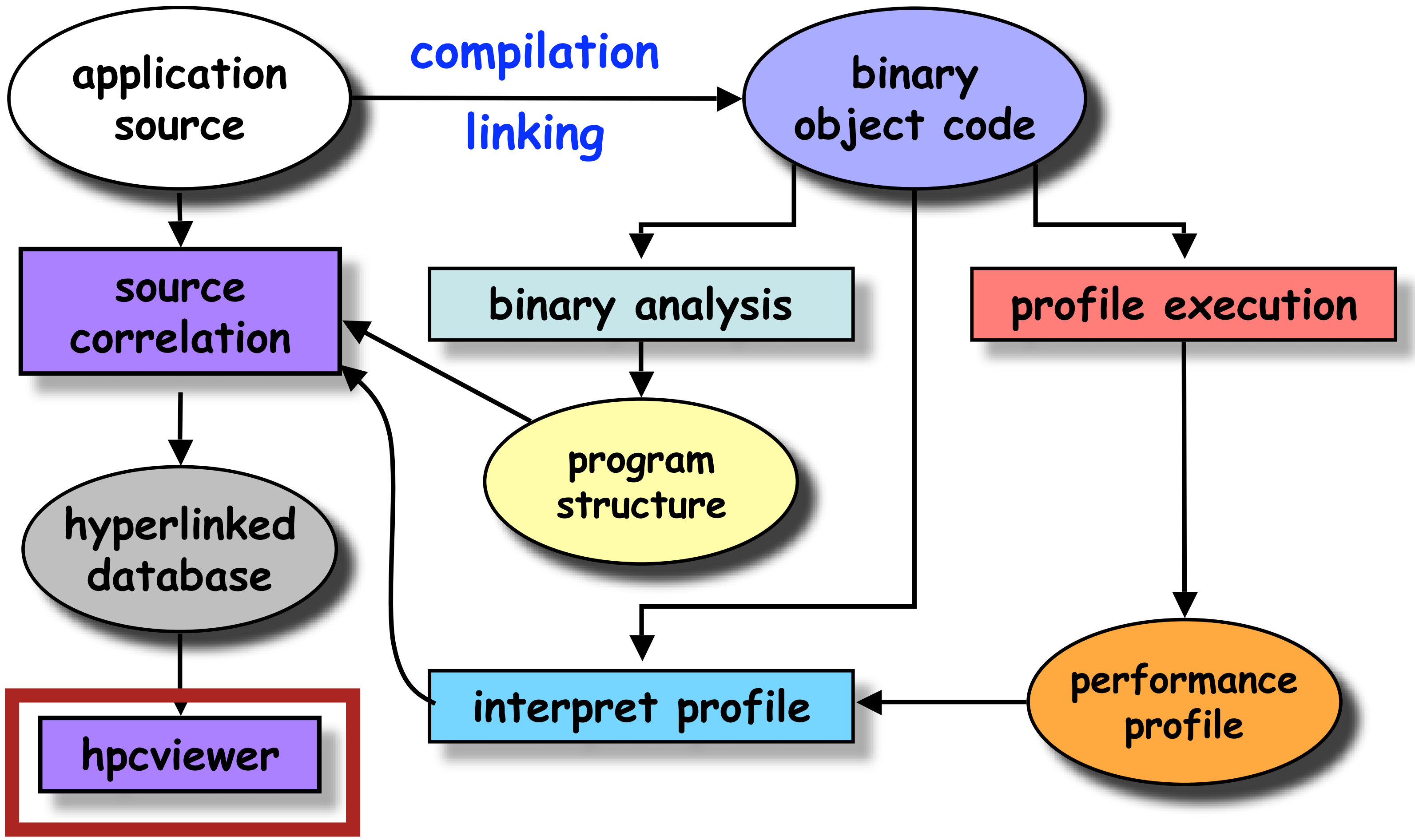
HPCToolkit Workflow



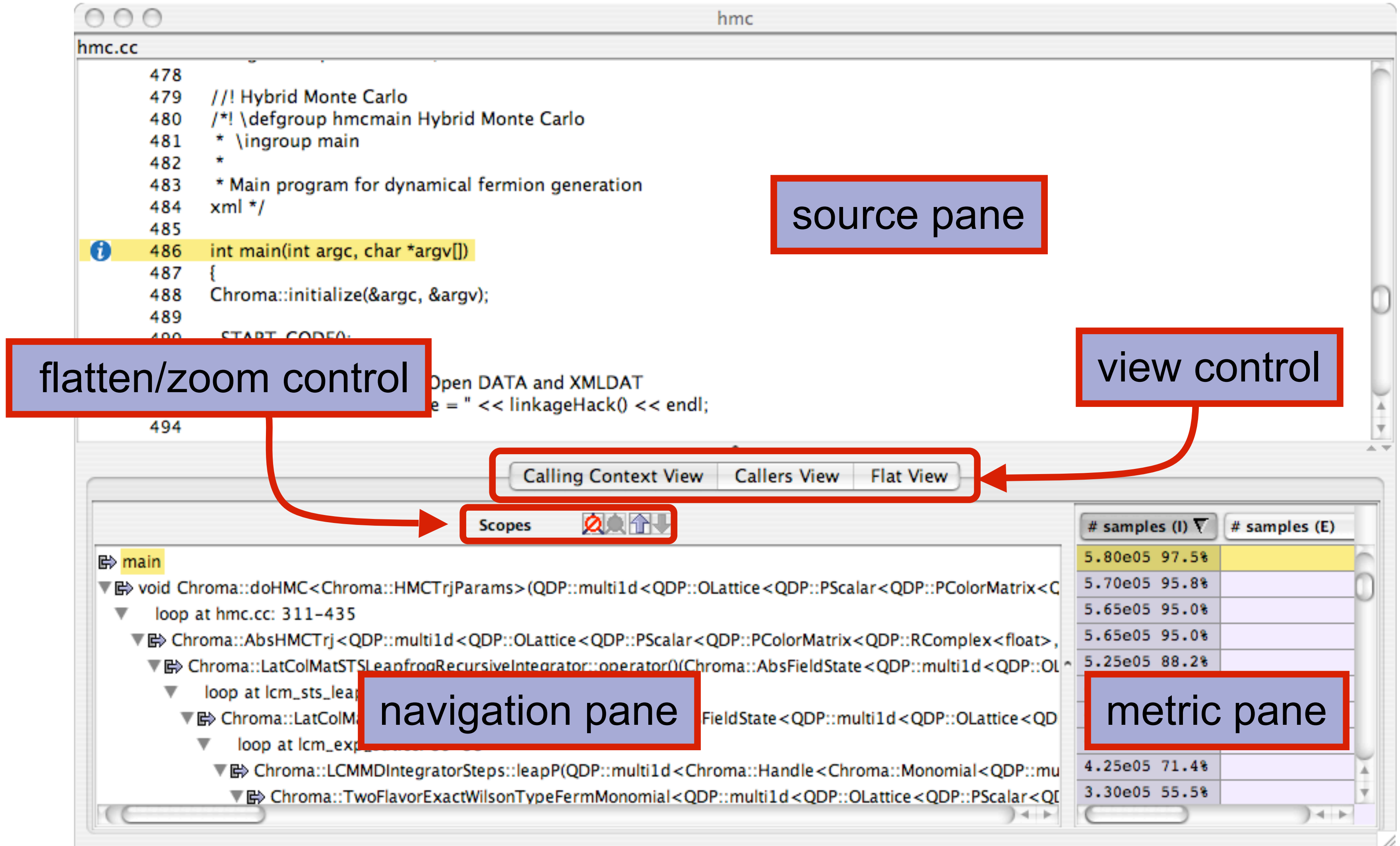
Data Correlation

- Problem
  - any one performance measure provides a myopic view
    - some measure potential causes (e.g. cache misses)
    - some measure effects (e.g. cycles)
    - cache misses not always a problem
  - event counter attribution is often inaccurate
- Approaches
  - multiple metrics for each program line
  - computed metrics, e.g. peak FLOPs - actual FLOPS
    - eliminates mental arithmetic
    - serves as a key for sorting
  - hierarchical structure
    - errors with line level attribution still yield good loop-level information

HPCToolkit System Overview



hpcviewer User Interface



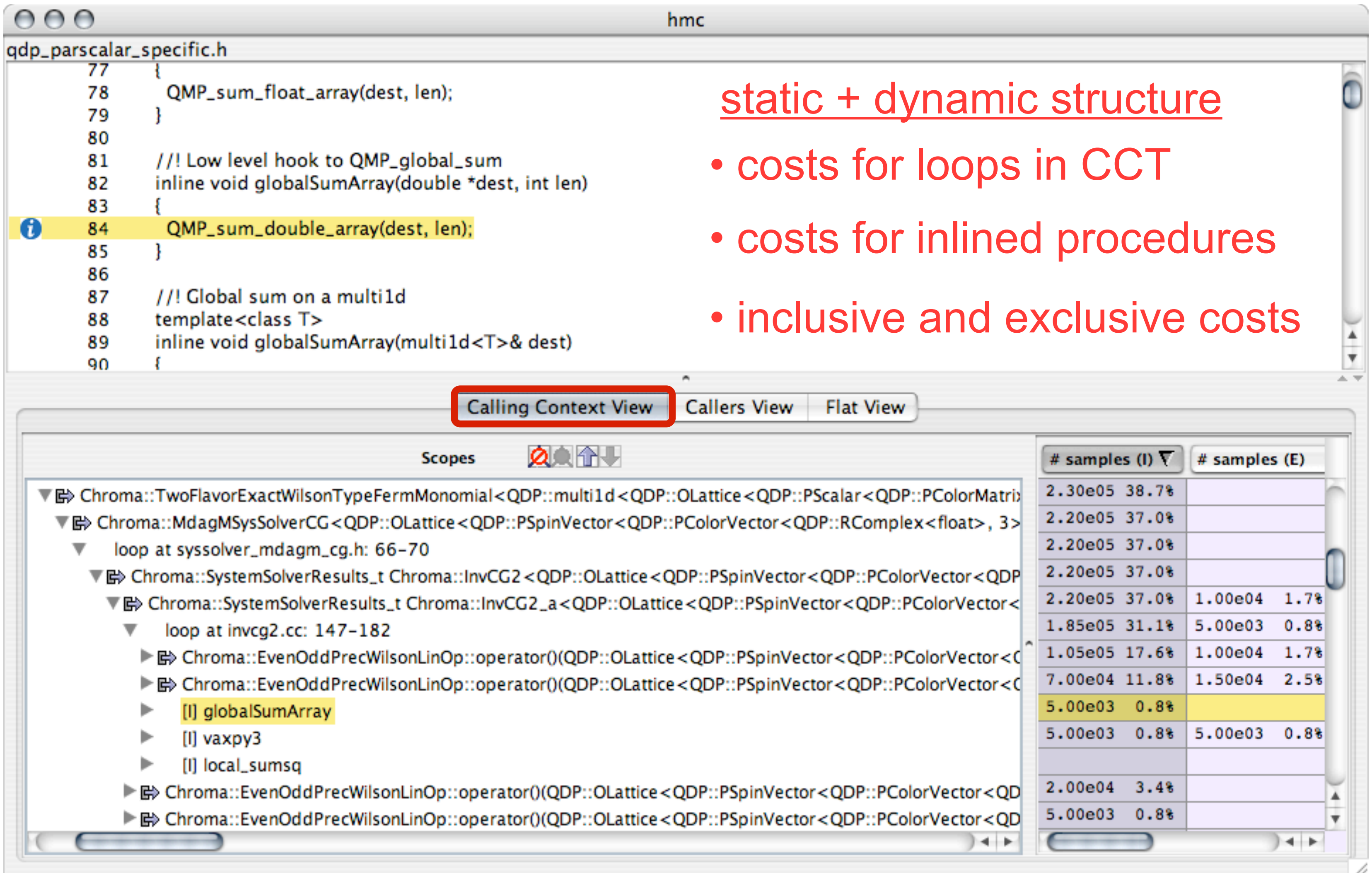
hpcviewer Views

- Calling context view
  - top-down view shows dynamic calling contexts in which costs were incurred
- Caller's view
  - bottom-up view apportions costs incurred in a routine to the routine's dynamic calling contexts
- Flat view
  - aggregates all costs incurred by a routine in any context and shows the details of where they were incurred within the routine

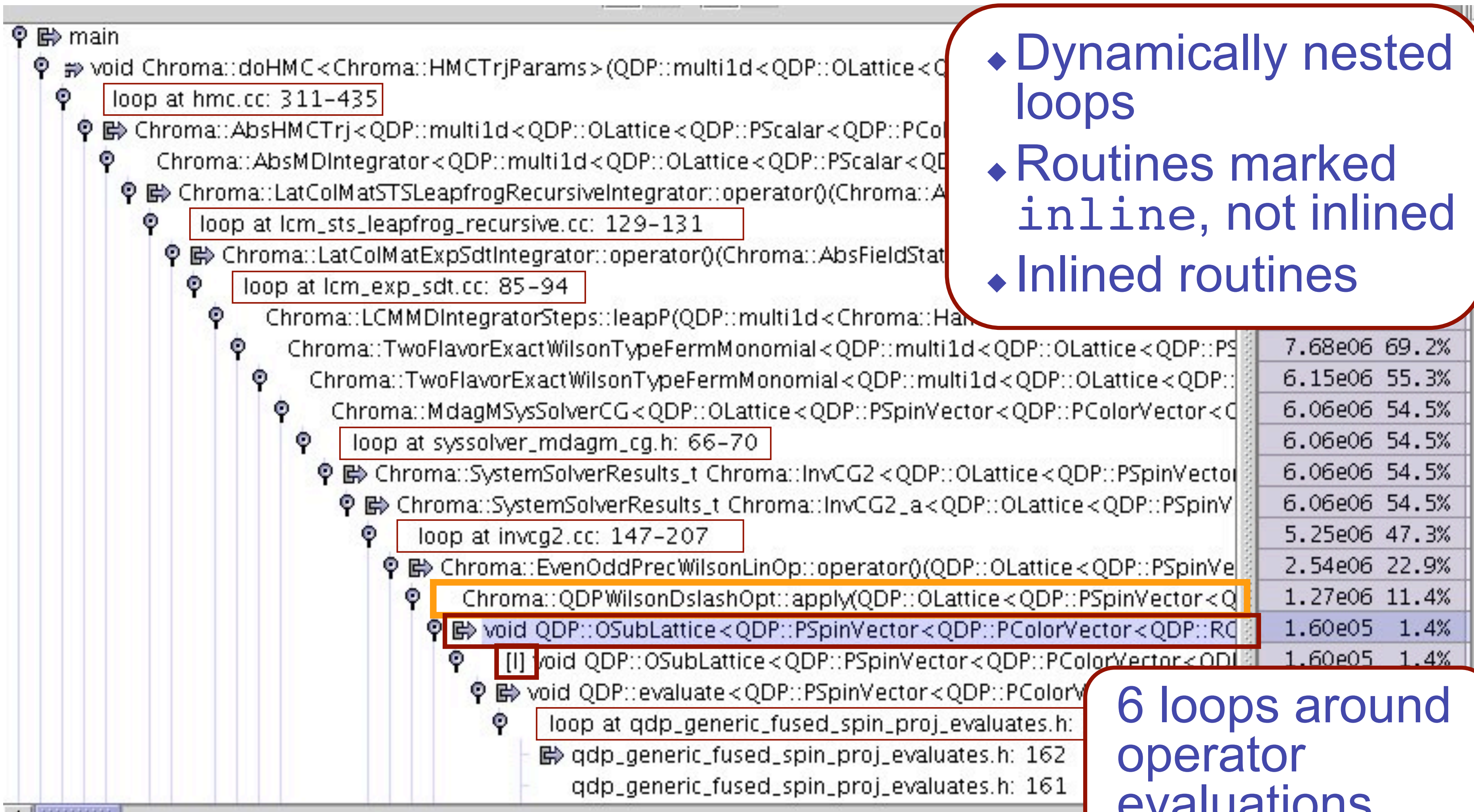
Calling Context View: Chroma Lattice QCD

static + dynamic structure

- costs for loops in CCT
- costs for inlined procedures
- inclusive and exclusive costs



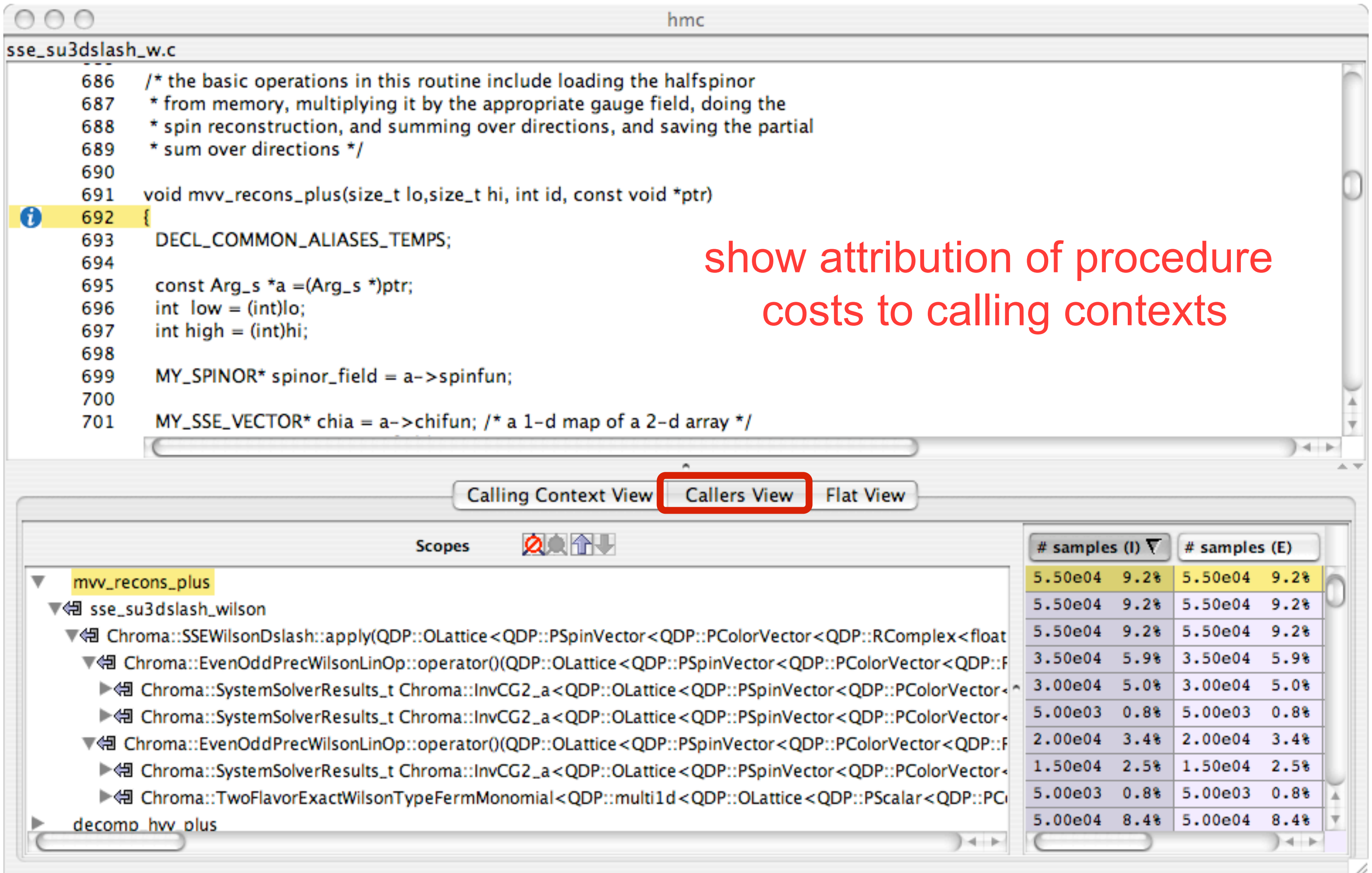
Fusing Static + Dynamic Structure: Chroma



- Dynamically nested loops
- Routines marked `inline`, not inlined
- Inlined routines

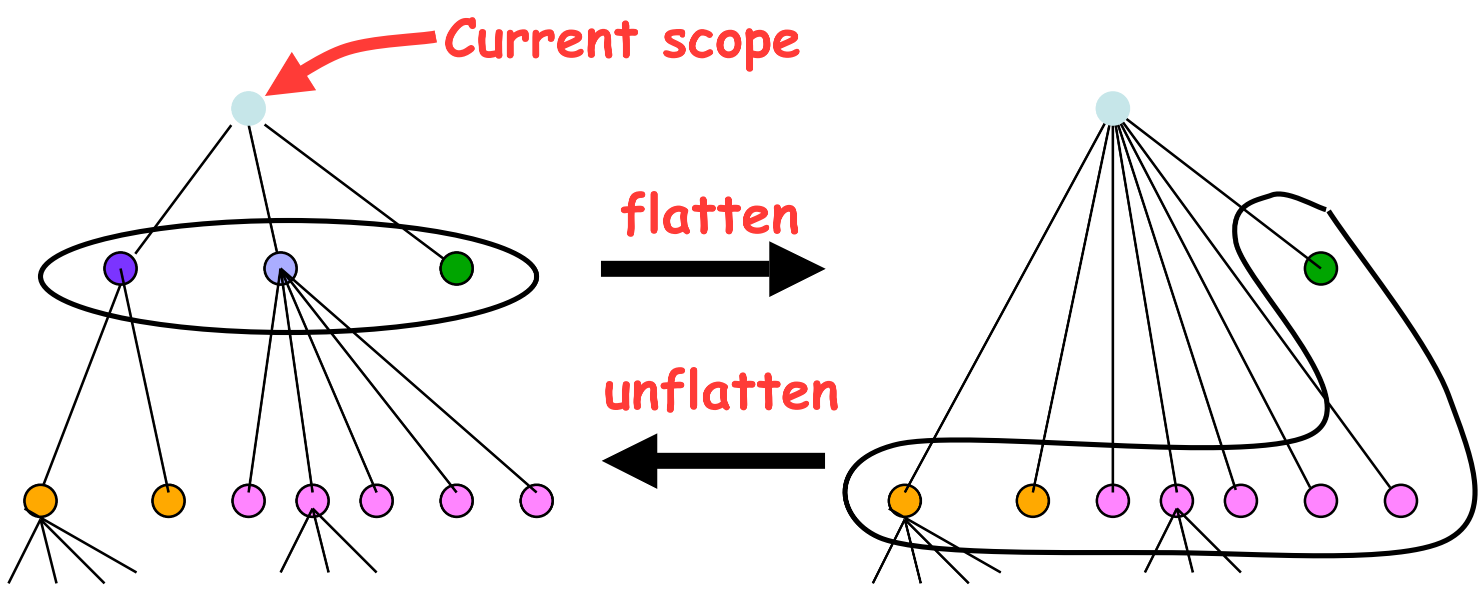
6 loops around operator evaluations

Caller’s View: Chroma Lattice QCD

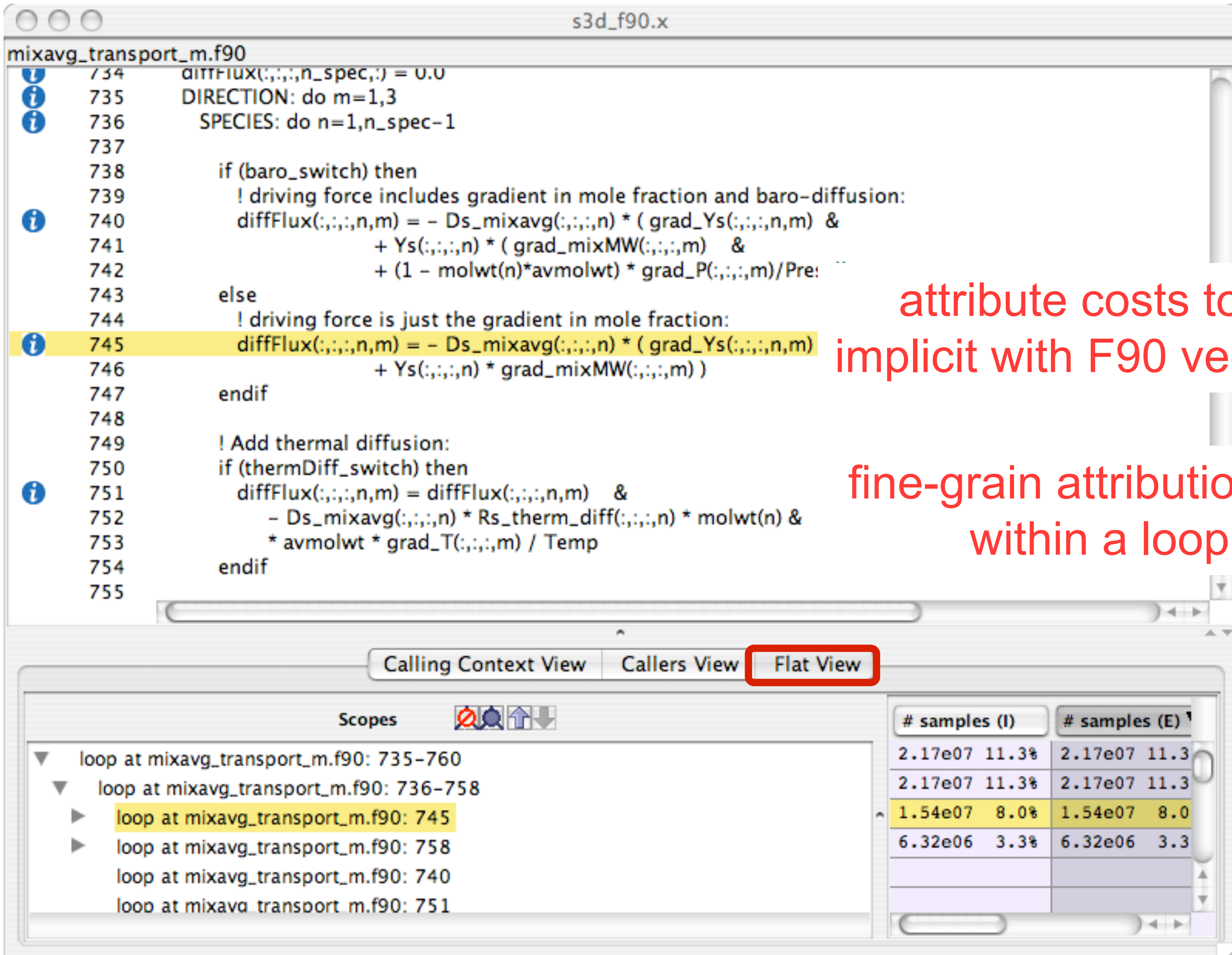


Flattening Static Hierarchies

- Problem
  - hierarchical view of a program is too rigid
  - sometimes want to compare children of different parents
    - e.g. compare all loops, regardless of the routine they are inside
- Solution
  - flattening elides a scope and shows its children instead



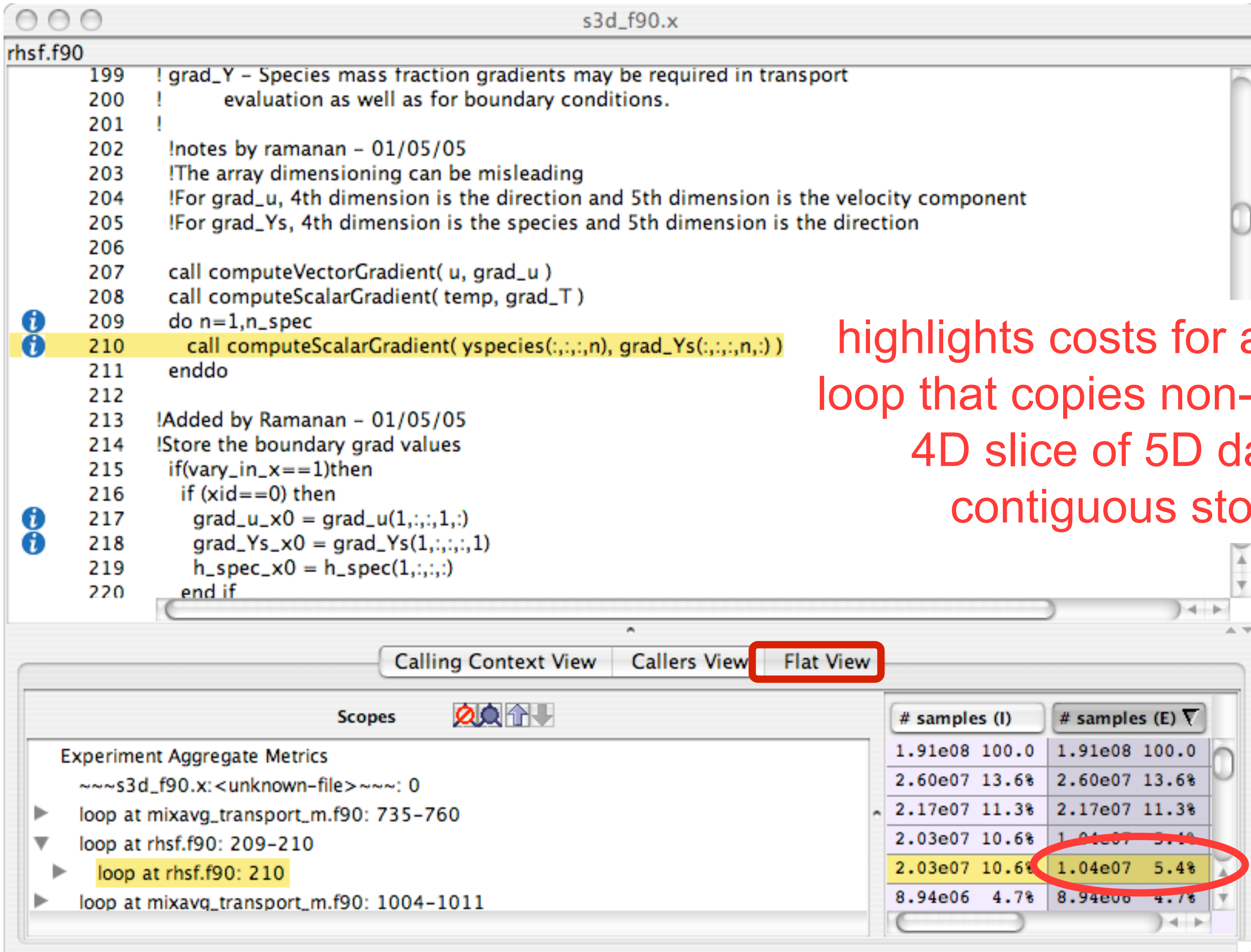
Flat View: S3D Combustion Code



attribute costs to loops implicit with F90 vector syntax

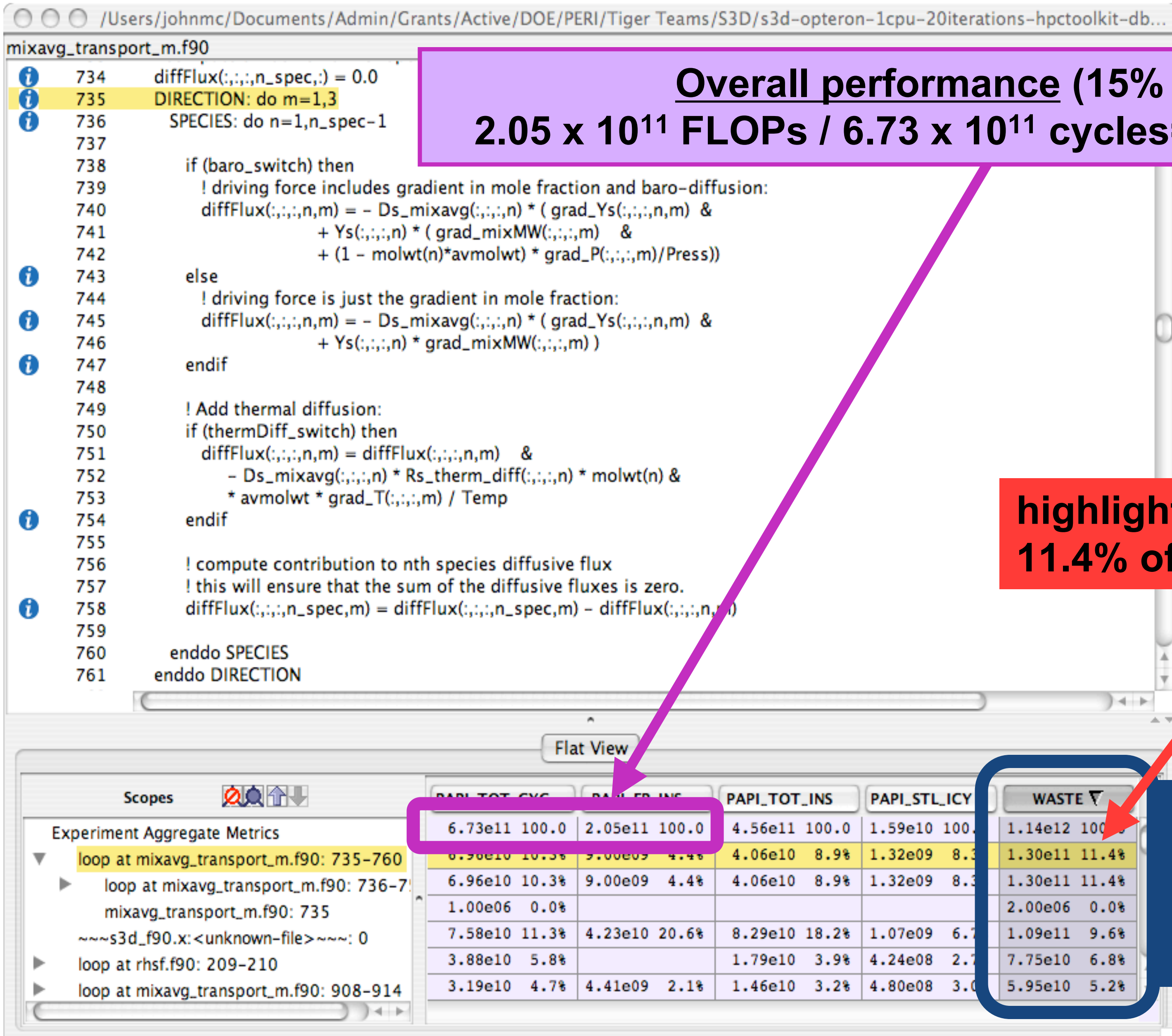
fine-grain attribution to loops within a loop nest

Another Flat View of S3D



highlights costs for an implicit loop that copies non-contiguous 4D slice of 5D data to contiguous storage

Computed Metrics for S3D



<u>Overall performance</u> (15% of peak)
2.05 x 10^{11} FLOPs / 6.73 x 10^{11} cycles= .305 FLOPs/cycle

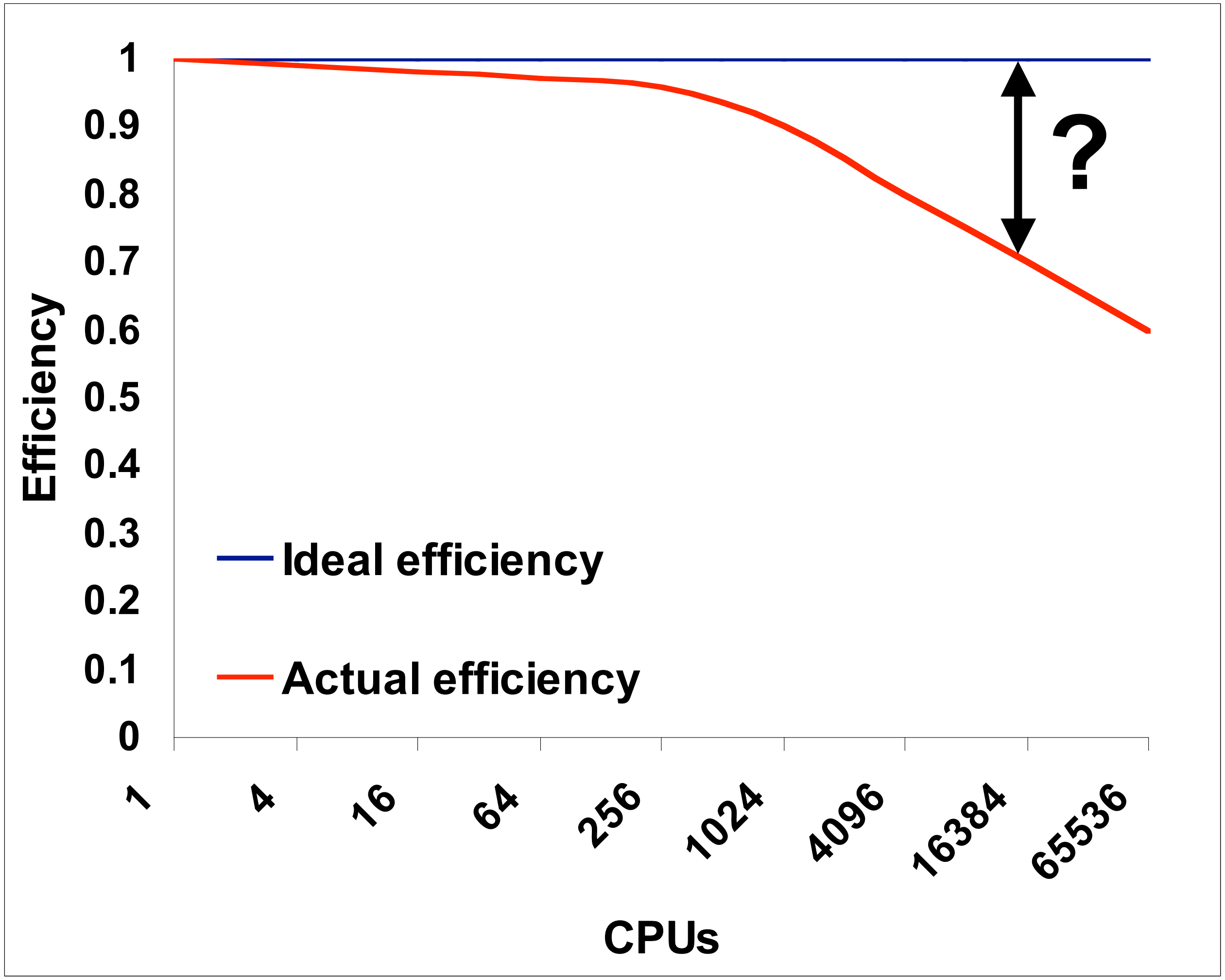
highlighted loop accounts for 11.4% of total program waste

<u>Wasted Opportunity</u> (Maximum FLOP rate * cycles - (actual FLOPs))

Outline

- Sampling based measurement
- Binary analysis
- User interface
- ☛ Scalability analysis
- Components
  - ours
  - our desires
- Related modeling activities

The Lump Under the Rug: Scaling Bottlenecks



Note: higher is better

Synthetic Example

Impediments to Scalability

- Communication overhead
  - synchronization
  - data movement
- Computation overhead
  - replicated initialization
  - partially replicated computation
- Parallelization deficiencies
  - load imbalance
  - serialization
- Algorithmic scaling
  - e.g. reductions: time increases as O(log *P*)

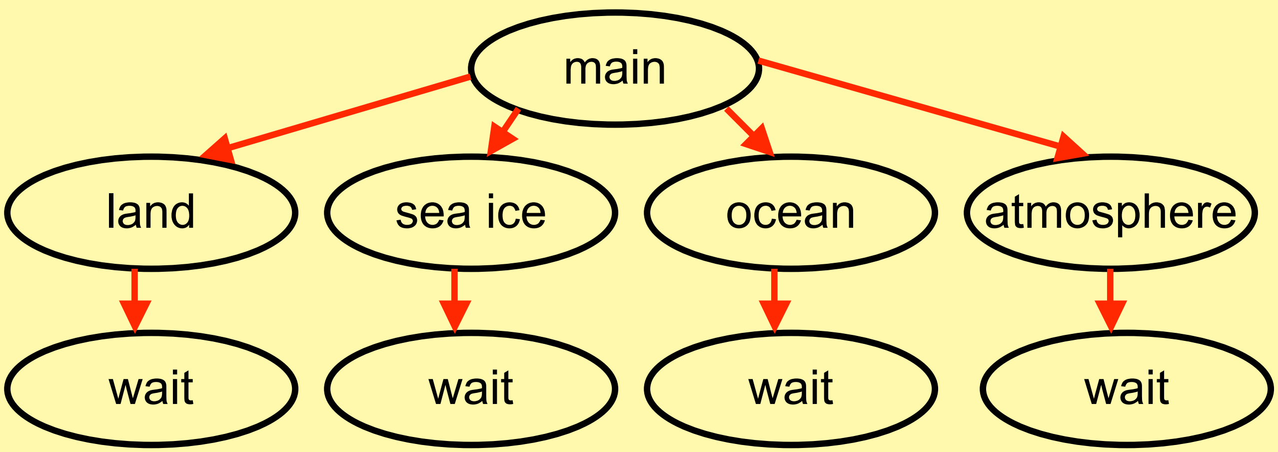
Goal: Automatic Scaling Analysis

- Pinpoint scalability bottlenecks
- Guide user to problems
- Quantify the magnitude of each problem
- Diagnose the nature of the problem

Challenges for Pinpointing Scalability Bottlenecks

- Parallel applications
  - modern software uses layers of libraries
  - performance is often context dependent
- Monitoring
  - bottleneck nature: computation, data movement, synchronization?
  - size of petascale platforms demands acceptable data volume
  - low perturbation for use in production runs

Example climate code skeleton



Performance Analysis with Expectations

- Users have performance expectations for parallel codes
  - strong scaling: linear speedup
  - weak scaling: constant execution time

- Putting expectations to work
  - define our expectations
  - measure performance under different conditions
    - e.g. different levels of parallelism or different inputs
  - compute the deviation from expectations for each calling context
    - for both inclusive and exclusive costs
  - correlate the metrics with the source code
  - explore the annotated call tree interactively

Weak Scaling Analysis for SPMD Codes

Performance expectation for weak scaling

- work increases linearly with # processors
- execution time is same as that on a single processor

- Execute code on p and q processors; without loss of generality, p < q
- Let T_i = total execution time on i processors
- For corresponding nodes n_q and n_p
  - let $C(n_q)$ and $C(n_p)$ be the costs of nodes n_q and n_p
- Expectation: $C(n_q) = C(n_p)$
- Fraction of excess work: $X_w(n_q) = \frac{\boxed{C(n_q) - C(n_p)}}{\boxed{T_q}}$

parallel overhead

total time

Strong Scaling Analysis for SPMD Codes

Performance expectation for strong scaling

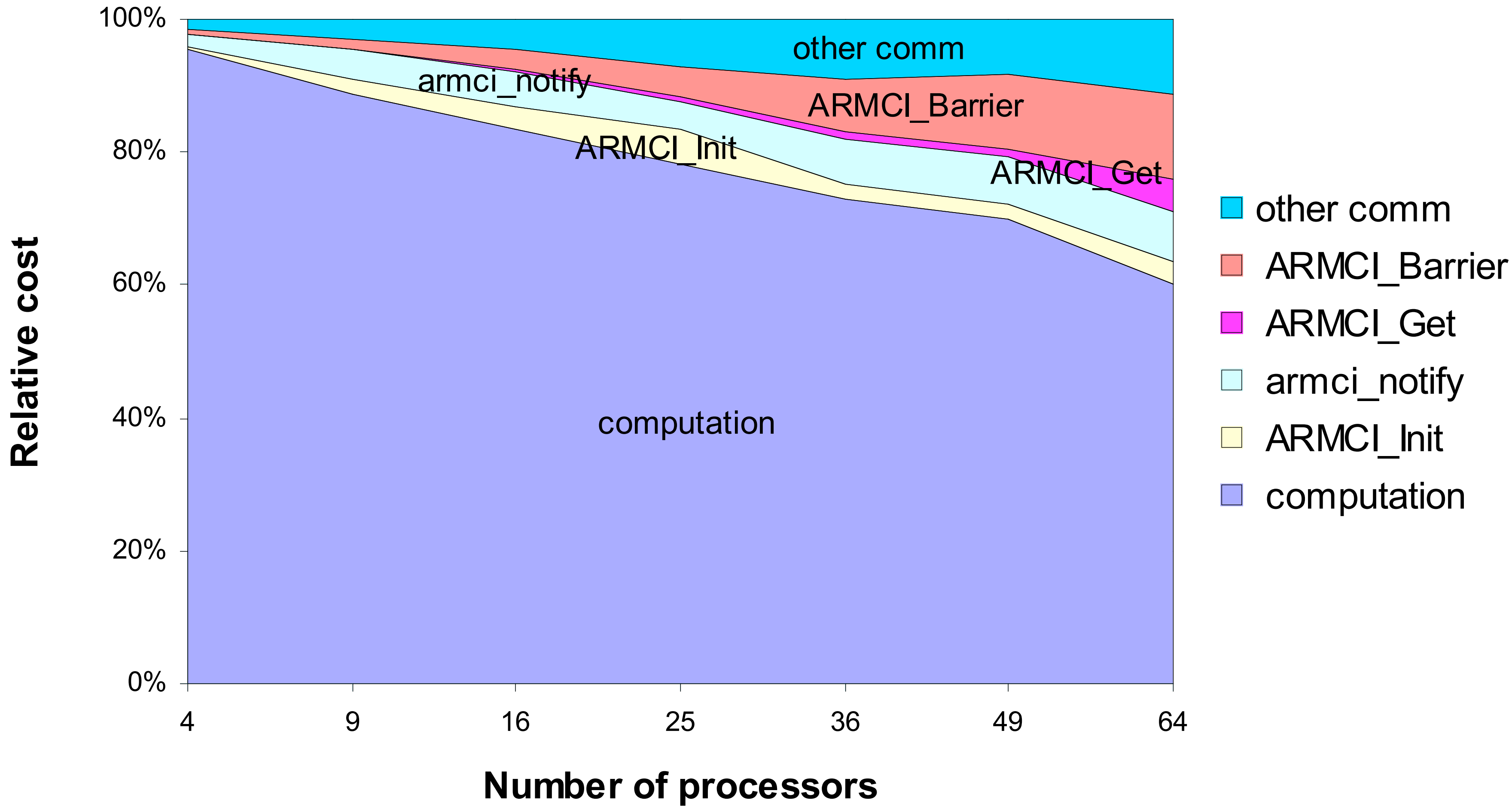
- work is constant
- execution time decreases linearly with # processors

- Execute code on p and q processors; without loss of generality, p < q
- Let T_i = total execution time on i processors
- For corresponding nodes n_q and n_p
  - let $C(n_q)$ and $C(n_p)$ be the costs of nodes n_q and n_p
- Expectation: $qC_q(n_q) = pC_p(n_p)$
- Fraction of excess work: $X_s(C,n_q) = \frac{\boxed{qC_q(n_q) - pC_p(n_p)}}{\boxed{qT_q}}$ parallel overhead / total time

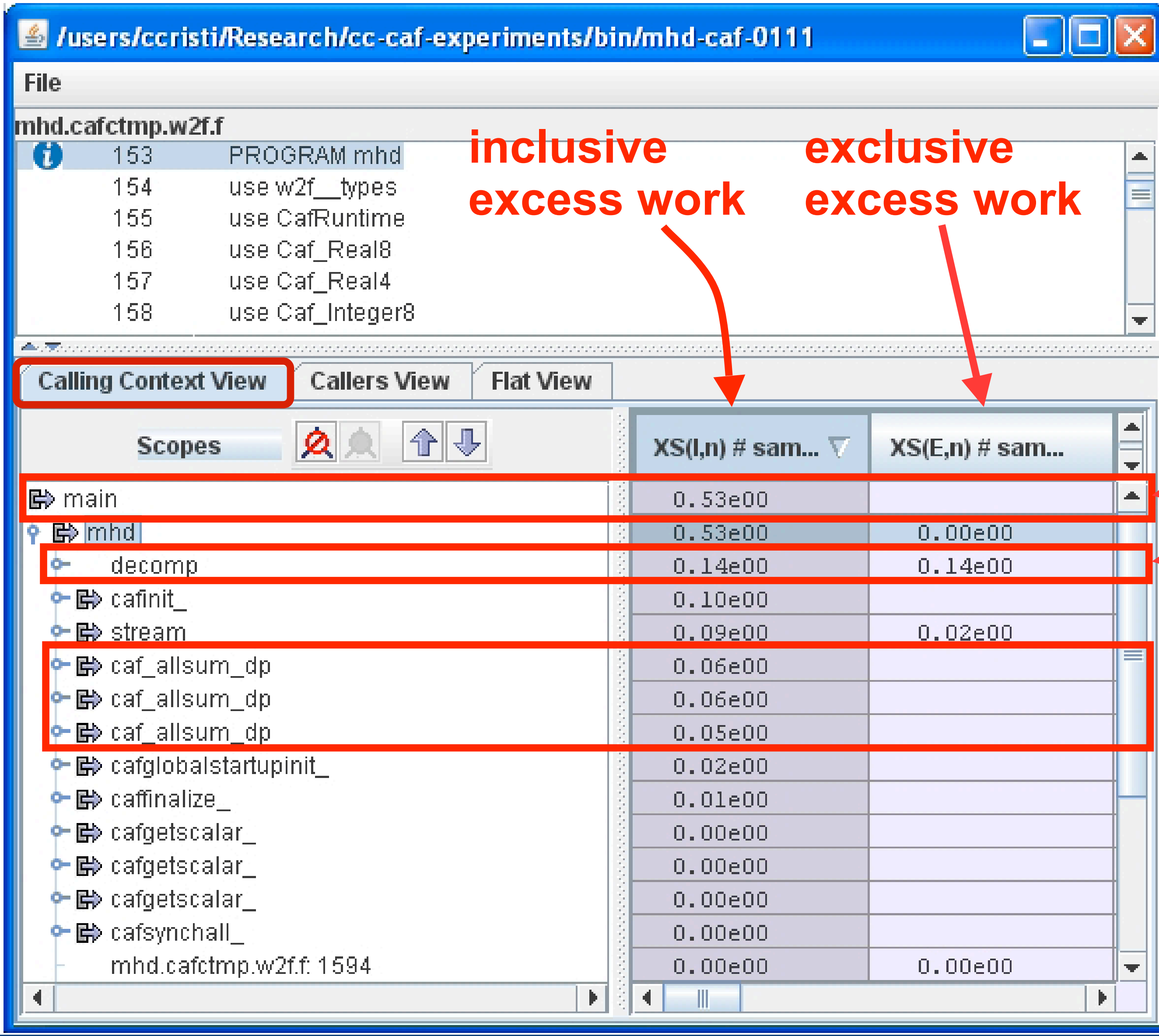
Scaling Analysis with Expectations

- Excess work metrics are intuitive
  - = 0 ideal scaling
  - > 0 suboptimal scaling
- Using excess work metrics
  - – $X(I,n) \approx X(E,n)$: scaling loss due to computation in n
  - – $X(I,n) >> X(E,n)$: scaling loss due n's callees
  - – using multiple views
    - losses associated with few calling contexts ⇒ CCT view suffices
    - losses spread across many contexts ⇒ use callers view

LBMHD size 1024^2



Strong Scaling Analysis of LBMHD

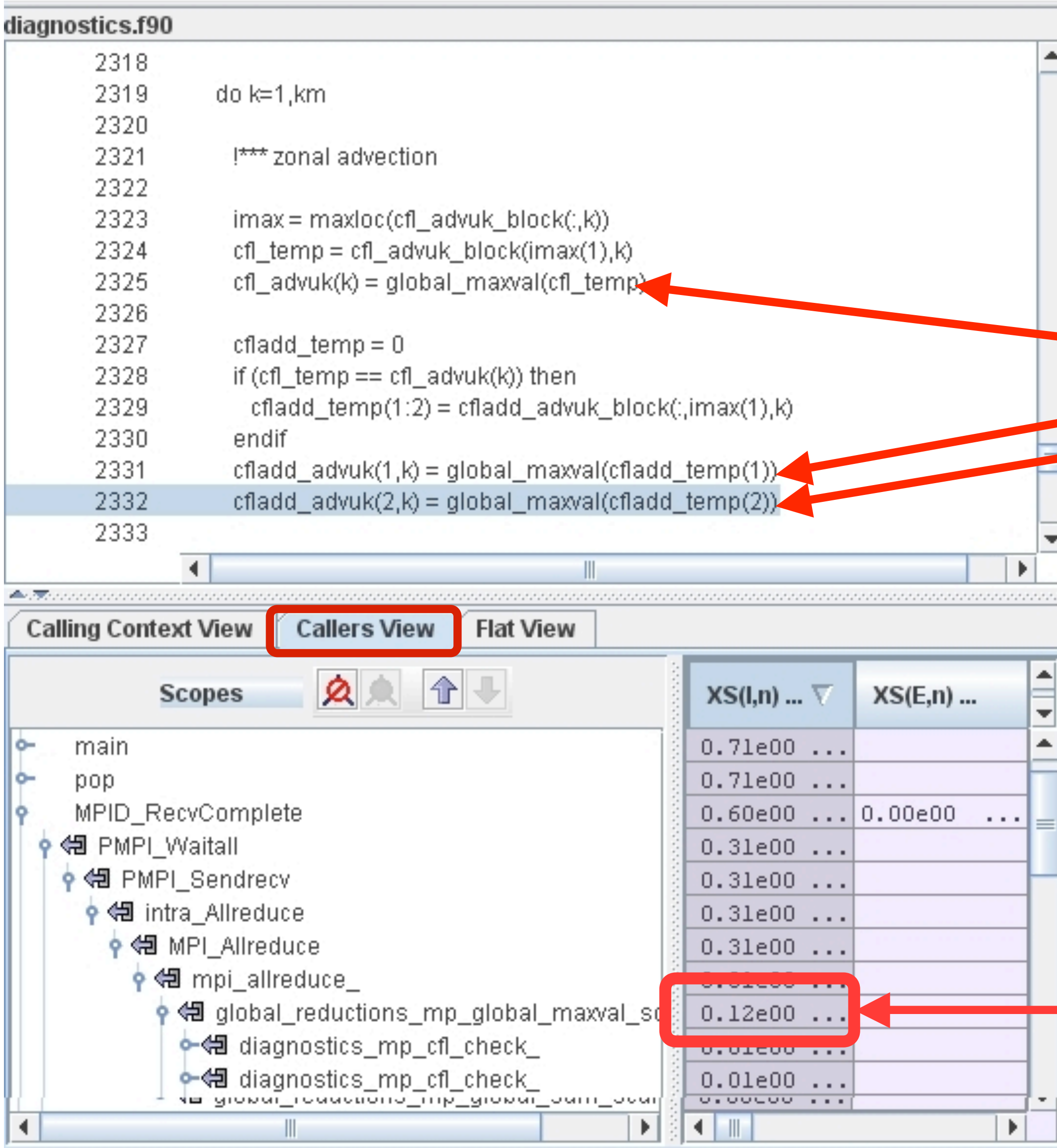


53% excess work = 47% efficiency

14% scalability loss due to computation

17% scalability loss due to barrier-based reductions

LANL's Parallel Ocean Program (POP)

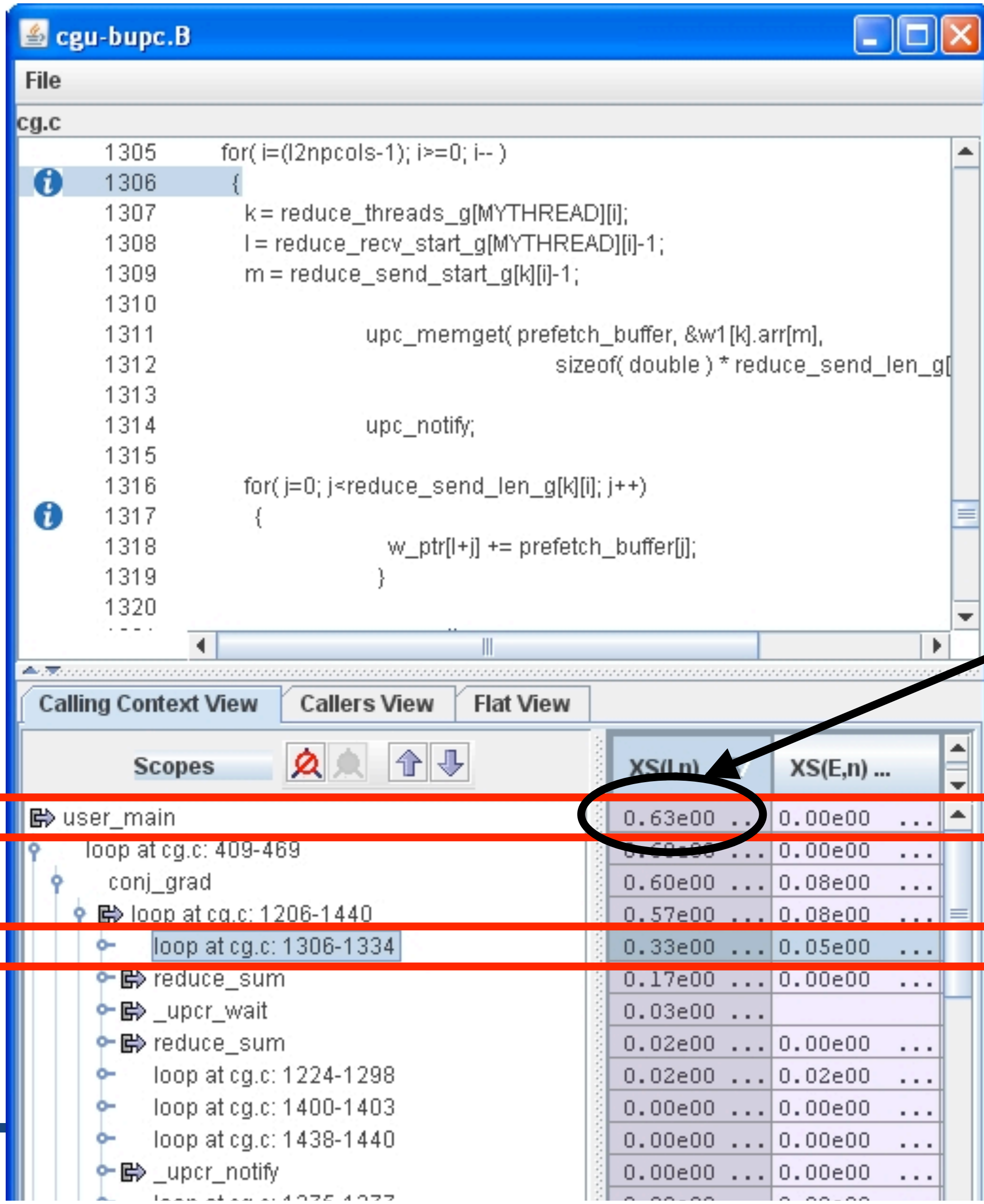


successive global reductions on scalars degrade parallel efficiency (7 total)

12% loss in scaling due to scalar reductions

7% in this routine alone

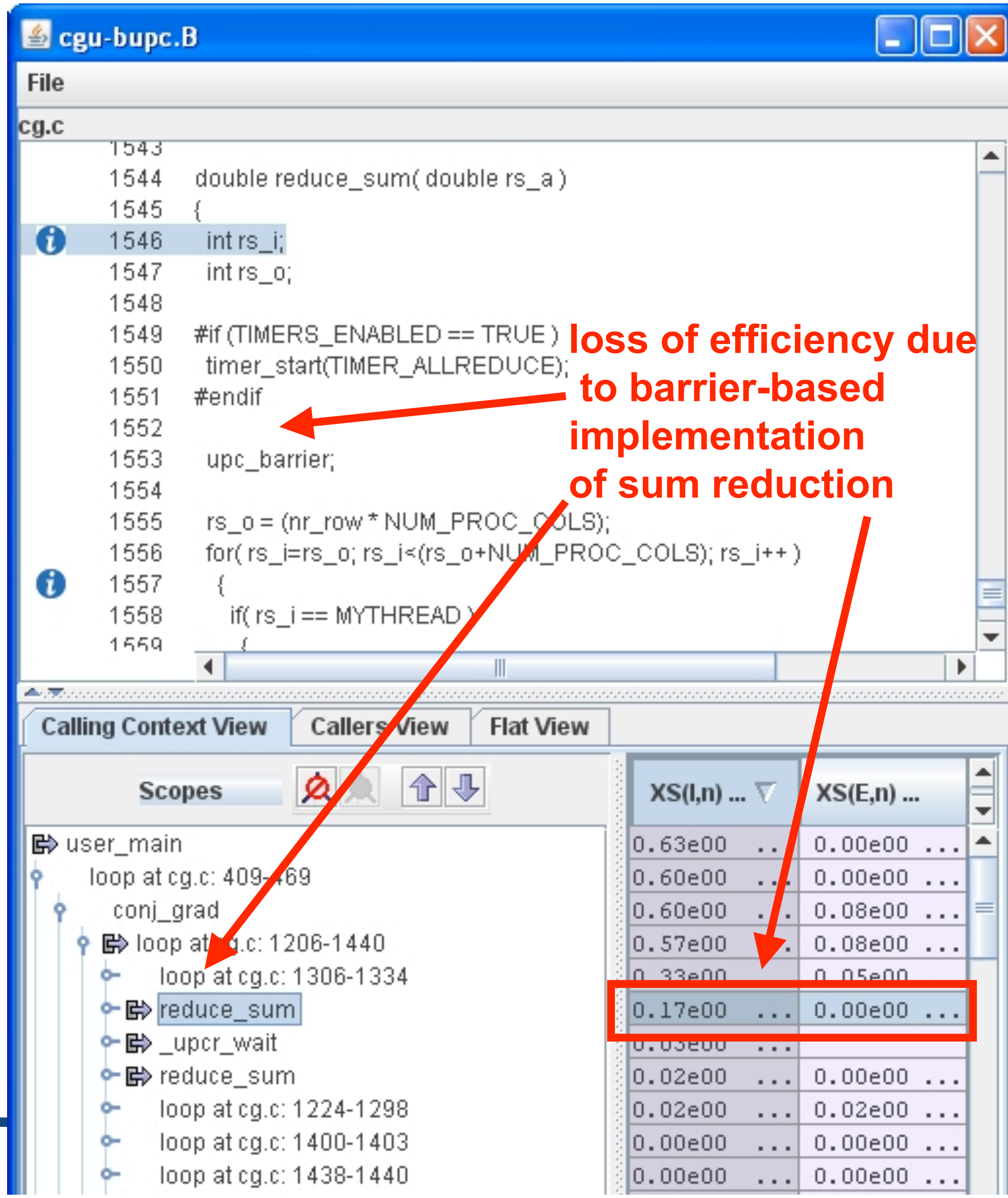
UPC NAS CG class B (size 75000)



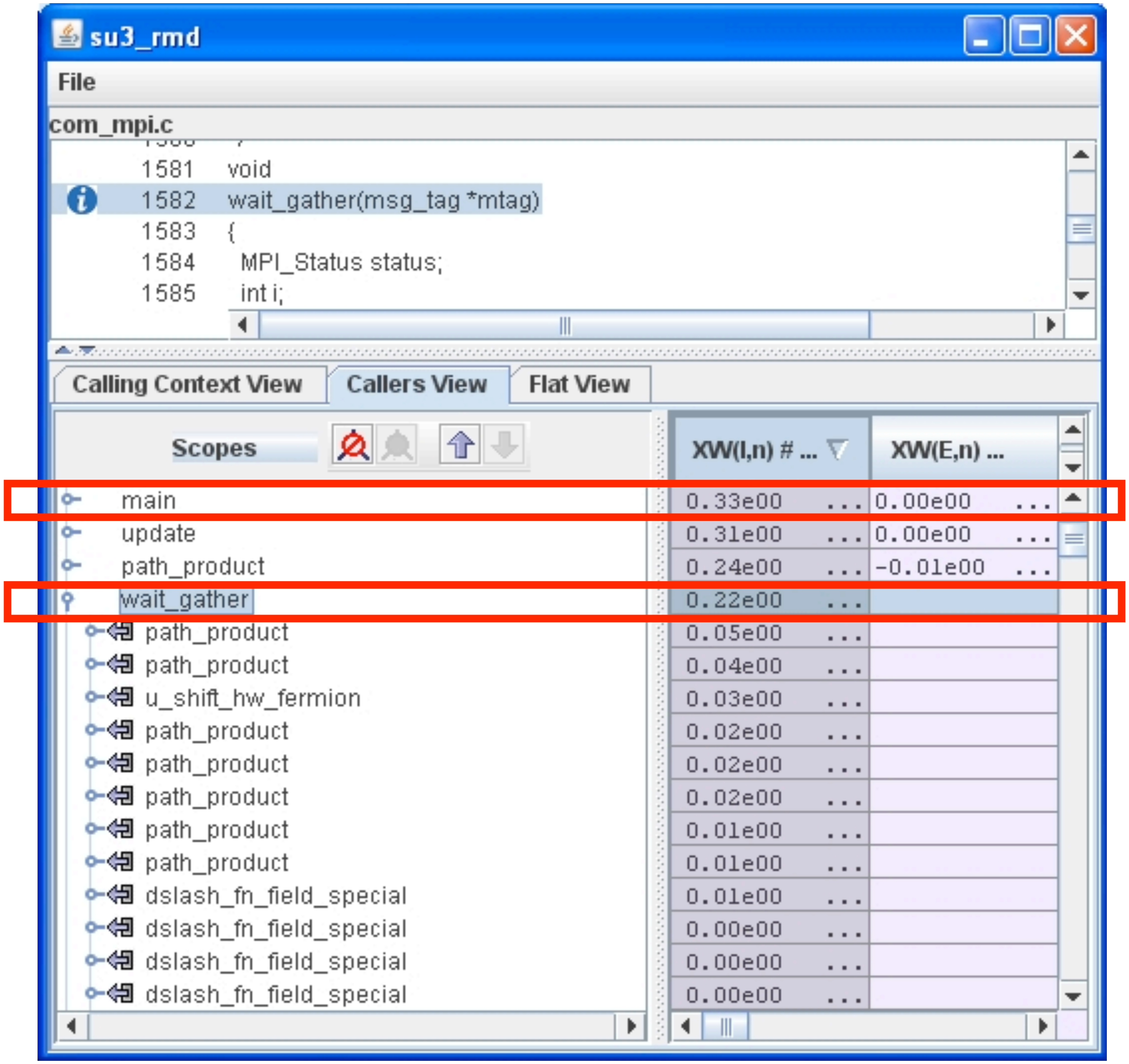
63% excess work = 36% efficiency

Remote data prefetch

UPC NAS CG class B (size 75000)



Weak Scaling Analysis of MILC's su3_rmd



Scalability Analysis Using Expectations

- Broadly applicable
  - independent of programming model
  - independent of bottleneck cause
  - applicable to a wide range of applications and architectures
- Easy to understand and use
  - fraction of excess work is intuitive and relevant metric
  - attribution to calling context enables precise diagnosis of bottlenecks
  - provides quantitative feedback
- Perfectly suited to petascale systems
  - call stack sampling is efficient enough for production use
  - uses only local performance information
  - data volume is modest and scales linearly
- Drawback
  - pinpoints bottleneck, but provides no intuition into cause

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Components to Share

- libmonitor - infrastructure for augmenting program with monitoring
  - what
    - monitors program launch thread creation/termination, fork/exec, exit
  - how
    - preloaded library for dynamically linked executables
    - static library for statically-linked executables
- hpcviewer user interface
  - three views: calling context, caller’s view, flat view
  - scalability analysis
- bloop binary analyzer
  - identify loops, inlined code
- OpenAnalysis - representation-independent program analysis tools
  - call graph and control-flow graph construction
  - dataflow analysis

Component Needs

- Metadata collection
- Standard OS interface for sampling-based measurement
- Ubiquitous stack unwinder for fully-optimized code
  - instruction cracker
  - engine for recovering frame state info at any point in an execution

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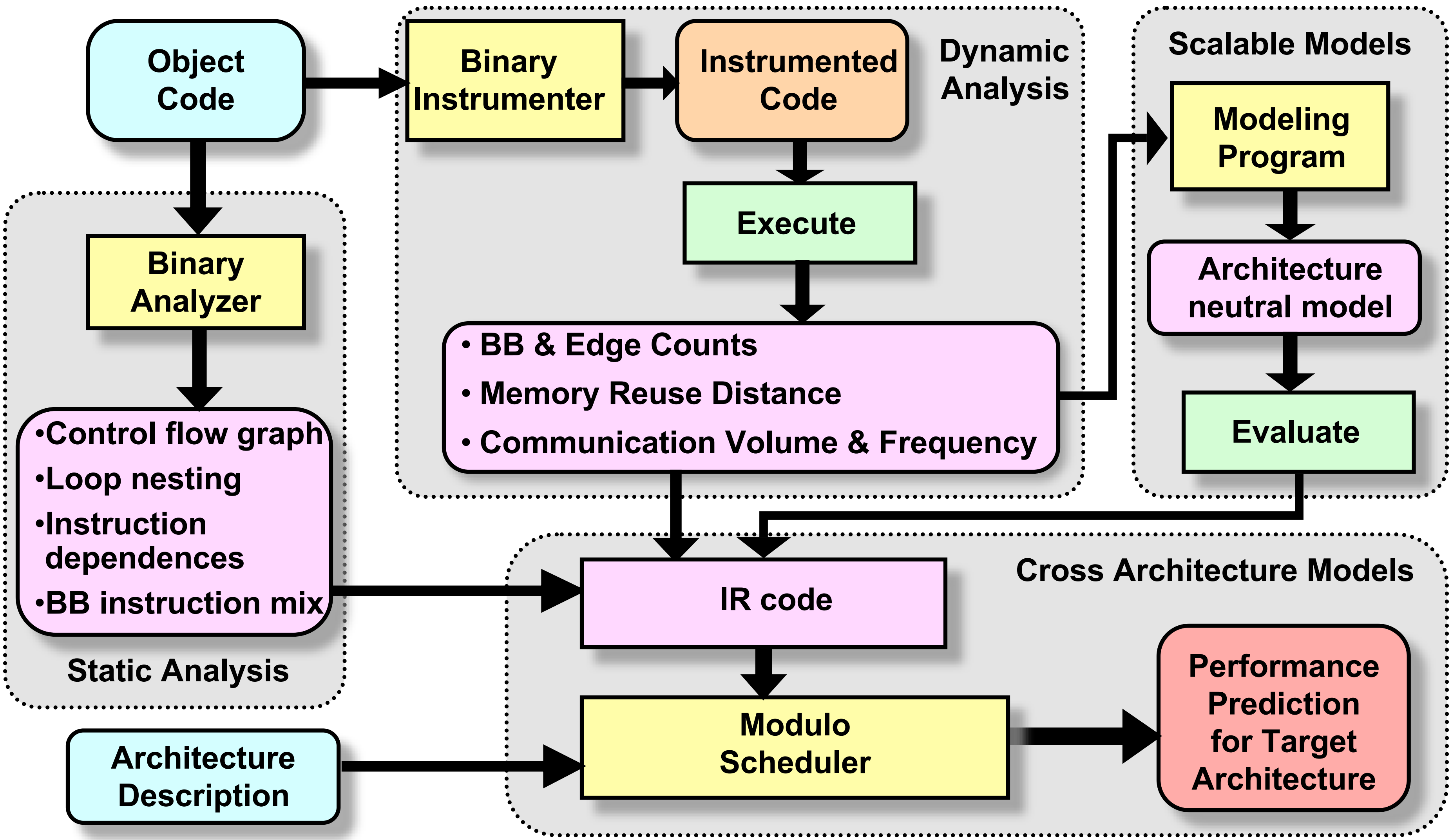
Analysis and Modeling of Node Performance



Capabilities of Modeling Toolkit

Loop level attribution of metrics

- Attribute execution costs to underlying causes
  - data dependencies that serialize operations
  - insufficient CPU resources
  - memory delays (latency and bandwidth)
- Explain patterns of data reuse
  - pinpoint opportunities for enhancing temporal reuse
  - pinpoint low spatial reuse
- Automatic “what if” scenarios
  - infinite number of CPU resources
  - no register or memory dependencies
  - no memory delays