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System and Parallel Programming

Prof. Dr. Felix Wolf

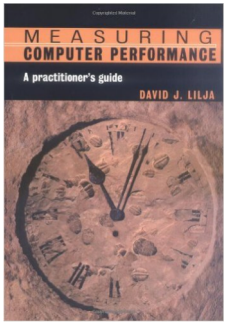
PERFORMANCE ANALYSIS

Outline

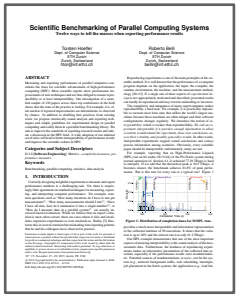
- Introduction
- Performance measurement
- Performance analysis
- Performance modeling

Literature

- Measuring Computer Performance - A Practitioner's Guide
  David J. Lilja, Cambridge University Press, 2000



- Torsten Hoefler, Roberto Belli: Scientific benchmarking of parallel computing systems: twelve ways to tell the masses when reporting performance results. Proc. of the SC15 Conference, 2015.



Charles Babbage, 1791 - 1871
(inventor of the first mechanical computer)

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"The most constant difficulty in contriving the engine has arisen from the desire to reduce the time in which the calculations were executed to the shortest which is possible."

Performance

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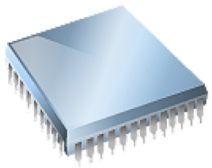
$$\textbf{Performance} \sim \frac{1}{\text{Resources to solution}}$$



Hardware

Time

Energy

… and ultimately

Money

Performance optimization pays off

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Example: HPC Service RWTH Aachen (2012)

~300 TFlops Bull/Intel cluster

Total cost of ownership (TCO) per year: **5.5** M€

Resource type	Fraction of TCO
Hardware	1/2
Energy	1/4
Staff	1/8
Others	1/8

Source: Bischof, an Mey, Iwainsky: Brainware for green HPC, Computer Science-Research and Development, Springer, 2012.

Tuning the workload by 1% will “save” 55k€ per year ~ 1 FTE

Trading runtime for energy

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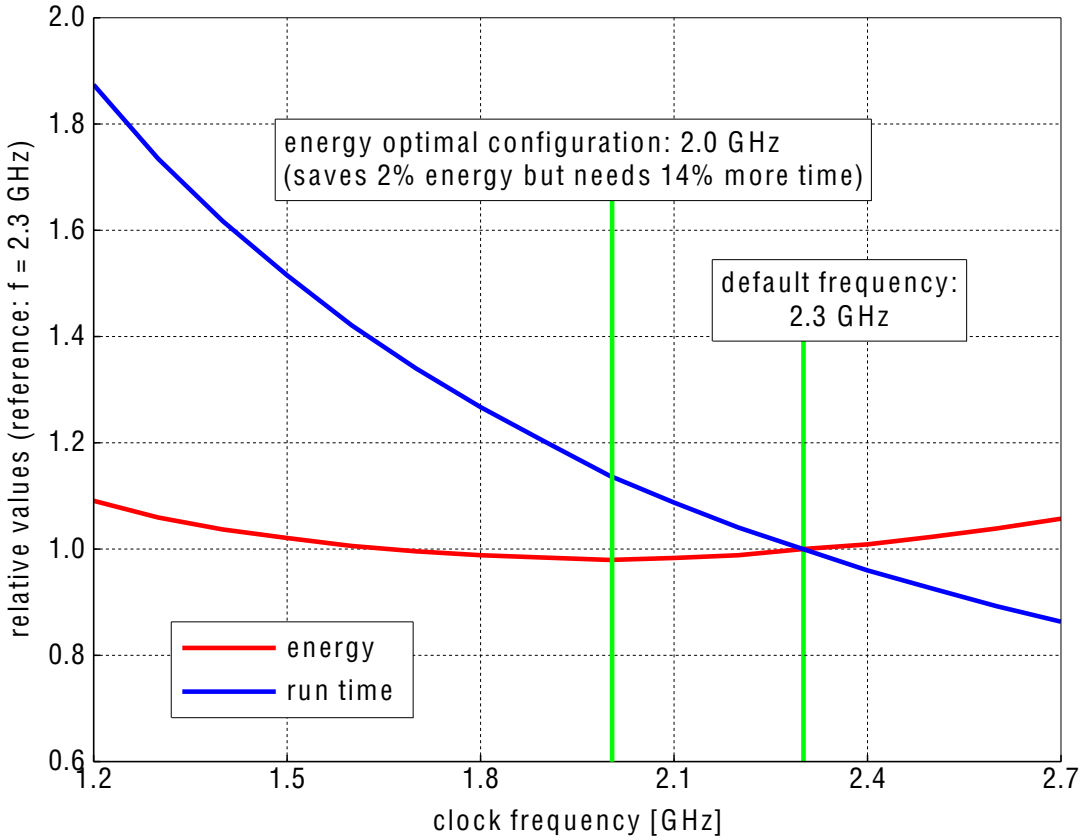
Runtime vs. energy for CFD code INDEED at different clock speeds



Are 2% less energy worth 14% more time?

Courtesy of GNS mbH

Energy delay product (EDP)

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Weighing runtime vs. energy largely a policy decision

$EDP = E * T^w$ - where E = energy, T = runtime, w = 1,2, or 3

The value of w determines how important performance is

- w=2 generally suggested for HPC
- Sometimes 2 not enough – especially for short runtimes

Energy-Efficient High Performance Computing: Measurement and Tuning. James H. Laros III, Kevin Pedretti, Suzanne M. Kelly, Wei Shu, Kurt Ferreira, John Van Dyke, Courtenay Vaughan, Spinger, 2013.

Different EDPs for INDEED

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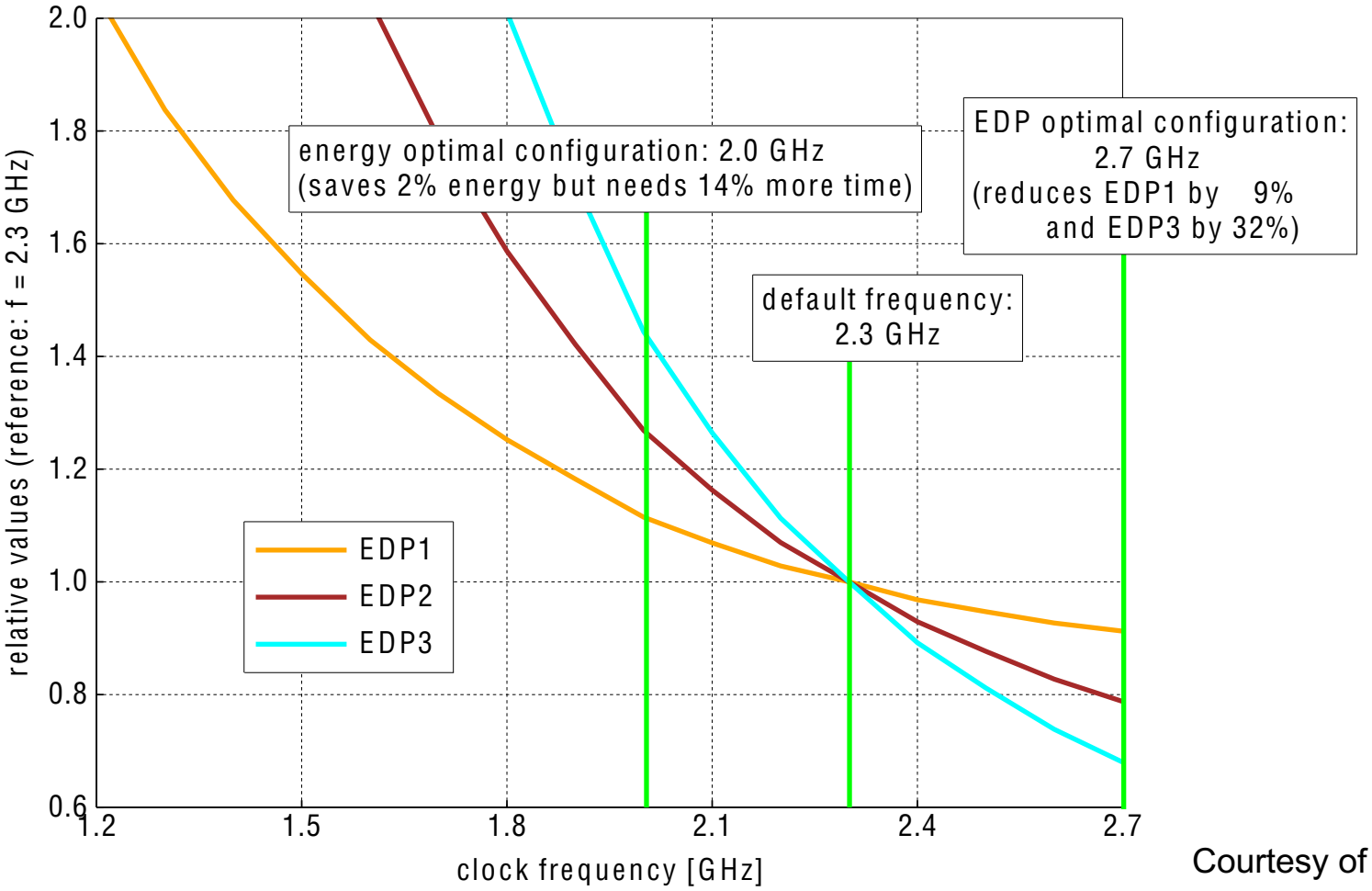

Courtesy of GNS mbH

Goals of performance analysis

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- **Compare alternatives** - which configurations are best under which conditions?
- **Determine the impact of a feature** – before-and-after comparison
- **System tuning** – find parameters that produce best overall performance
- **Identify relative performance** – which program / algorithm is faster?
- **Performance debugging** – search for bottlenecks
- **Set expectations** – provide information for users

Serial vs. parallel performance

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Serial programs

- Memory behavior
- Instruction-level parallelism

Parallel programs

- Amount of parallelism
- Granularity of parallel tasks
- Inter-task communication
- Inter-task synchronization
- Contention (e.g., for memory bandwidth)

Three basic performance analysis methods

- Analytical modeling
- Simulation
- Measurement

Analytical modeling

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- Mathematical description of the system
  - Allows quick change of parameters
  - Rapid solution
- Often requires restrictive assumptions, limiting accuracy
- Allows insights into fundamental properties such as scalability
- Can be used to set expectations for simulations or measurements
- Example
  - Memory delay $t_{avg} = ht_c + (1-h)t_m$
  - Parameters obtained from manufacturer or measurement

Simulation

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- Program written to model important features of the target system
- Can be easily modified to study the impact of changes
- Cost
  - Writing the program
  - Running the program
- Impossible to model every small detail
  - Simulation refers to “ideal” system; sometimes low accuracy
- Example
  - Cache simulator
  - Parameters: size, block size, associativity, cache and memory delays

Measurement

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- No simplifying assumptions
- Highest credibility
- Information only on specific system being measured
- Harder to change system parameters in a real system
- Difficult and time consuming
- Software tools can help
- Should be used in conjunction with modeling
  - Can aid the development of performance models
  - Performance models set expectations against which measurements can be compared

Comparison

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Measurement – Simulation – Model

Adapted from: T. Hoefler, W. Gropp, W. Kramer, and M. Snir. Performance modeling for systematic performance tuning. In State of the Practice Reports, SC '11, pages 6:1–6:12. ACM, 2011.

Comparison (2)

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	Analytical modeling	Simulation	Measurement
Flexibility	High	Medium	Low
Accuracy	Low	Medium	High
Cost / difficulty	Using a model is easy and cheap, developing one can be hard	The cost of running a simulator depends on the simulation, developing one is usually hard	Obtaining measurements requires skills & experience and can be expensive in terms of compute time

Metrics of performance

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What can be measured?

- A count of how many times an event occurs
  - Example: number of input / output requests
- The duration of some time interval
  - Example: duration of these requests
- The size of some parameter
  - Example: number of bytes transmitted or stored

Derived metrics

- E.g., rates / throughput
- Needed for normalization

Primary performance metrics

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- Execution time, response time
  - Time between start and completion of a program or event
  - Most consistent and reliable measure of performance
  - Wall-clock time vs. CPU time
- Throughput
  - Total amount of work done in a given time
- Problem: execution time often subject to run-to-run variation and therefore hard to reproduce exactly
  - Summarize multiple measurements

Alternative performance metrics

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- Clock rate
- Instructions executed per second
- FLOPS – floating-point operations per second
- Benchmarks
  - Standard test program(s) + standardized methodology
  - E.g., SPEC, Linpack
- QUIPS / HINT [Gustafson and Snell, 95]
  - Quality improvements per second
  - Quality of solution instead of effort to reach it

Peak performance

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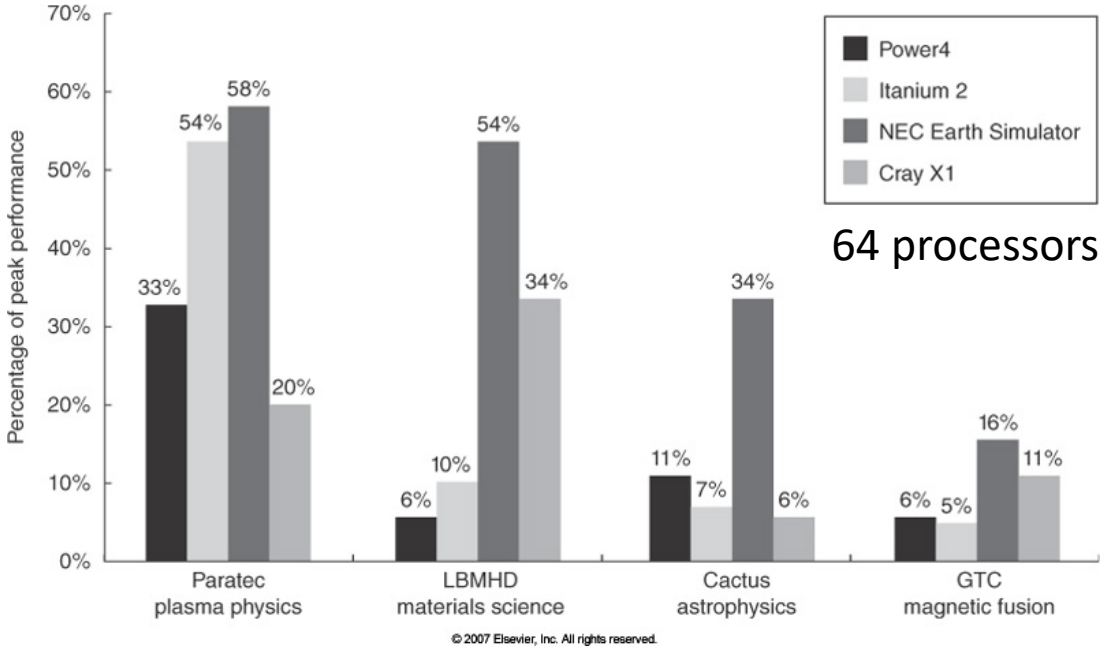
- Peak performance is the performance a computer is guaranteed not to exceed



Source: Hennessy, Patterson: Computer Architecture, 4th edition, Morgan Kaufmann

How to measure time?
UNIX gettimeofday()

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```
#include <sys/time.h>
#include <stdio.h>

double get_seconds()
{
  struct timeval tv;
  gettimeofday(&tv, NULL);
  return tv.tv_sec + tv.tv_usec * 1.0e-6;
}

int main()
{
  double start = get_seconds();
  /* do some work */
  double end = get_seconds();
  printf("Time: %f seconds\n", end-start);
}
```

Further timers

Function	Description	Standard
clock()	Approximation of processor time	ANSI-C
times()	Wall-clock time; system and user time	UNIX / IEEE
getrusage()	User time, system time, memory usage, page faults, etc.	UNIX / BSD
MPI_Wtime()	Wall-clock time	MPI
`omp_get_wtime()`	Wall-clock time	OpenMP

Insufficiently synchronized clocks on clusters

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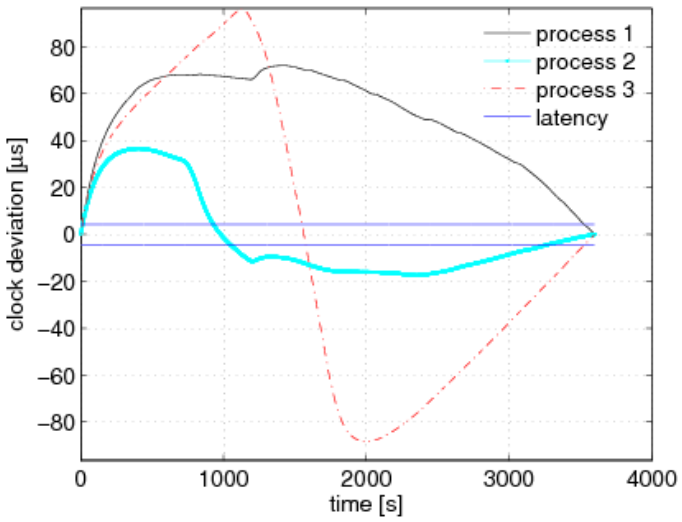
- Clocks on a cluster may differ in terms
  - Offset at a given time
  - Drift (i.e., speed)
- Drift often unstable
  - Due to temperature variation or NTP synchronization
  - Linear interpolation may not be enough to preserve logical event order



Clock deviation after linear interpolation

Summarizing (deterministic) results

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What?	Example	How?
Costs	Flop count; execution time (in certain scenarios)	• Arithmetic mean $\bar{x} = \frac{1}{n}\sum_{i=1}^{n} x_i$
Rates	FLOP/s	• Ideally arithmetic mean of numerator divided by arithmetic mean of denominator • Harmonic mean otherwise $\bar{x} = \frac{n}{\sum_{i=1}^{n} \frac{1}{x_i}}$

Torsten Hoefler, Roberto Belli: Scientific benchmarking of parallel computing systems: twelve ways to tell the masses when reporting performance results. Proc. of the SC15 Conference, 2015.

Summarizing (deterministic) results (2)

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What?	Example	How?
Unitless ratios	Speedup	• Don't. Summarize the costs or rates that the ratio is based on instead • Only if these are not available use the geometric mean $\bar{x} = \sqrt[n]{\prod_{i=1}^{n} x_i}$

harmonic mean ≤ geometric mean ≤ arithmetic mean

Torsten Hoefler, Roberto Belli: Scientific benchmarking of parallel computing systems: twelve ways to tell the masses when reporting performance results. Proc. of the SC15 Conference, 2015.

Non-deterministic results

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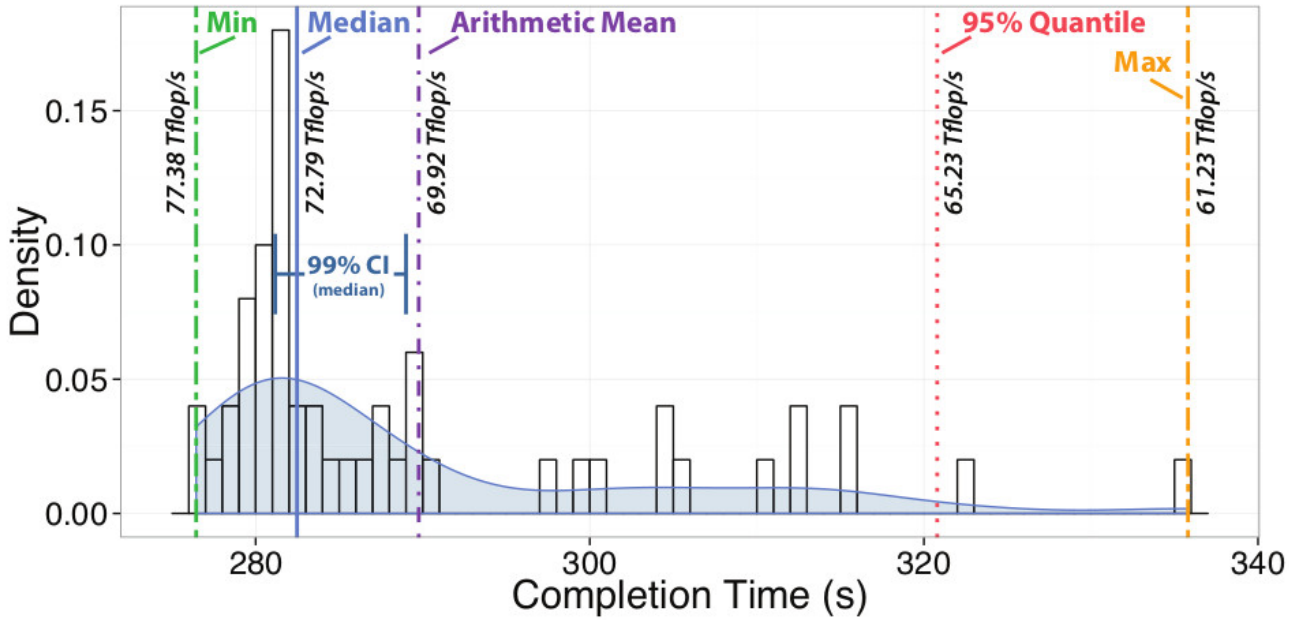
- Performance varies significantly on today's supercomputers
  - A single number may not represent the actual performance well
  - Some measure of spread or stability of the results is required (e.g., standard deviation)
- Report whether the measurement values are deterministic
  - For nondeterministic data, report confidence intervals of the measurement
  - Allows number of required measurements to be computed
- Do not assume normality of collected data (e.g., based on the number of samples) without diagnostic checking

Torsten Hoefler, Roberto Belli: Scientific benchmarking of parallel computing systems: twelve ways to tell the masses when reporting performance results. Proc. of the SC15 Conference, 2015.

Non-normal results

- For non-normal data use rank-based measures
  - Example: median, percentiles



Distribution of completion times for 50 HPL runs

Torsten Hoefler, Roberto Belli: Scientific benchmarking of parallel computing systems: twelve ways to tell the masses when reporting performance results. Proc. of the SC15 Conference, 2015.

Performance tuning cycle

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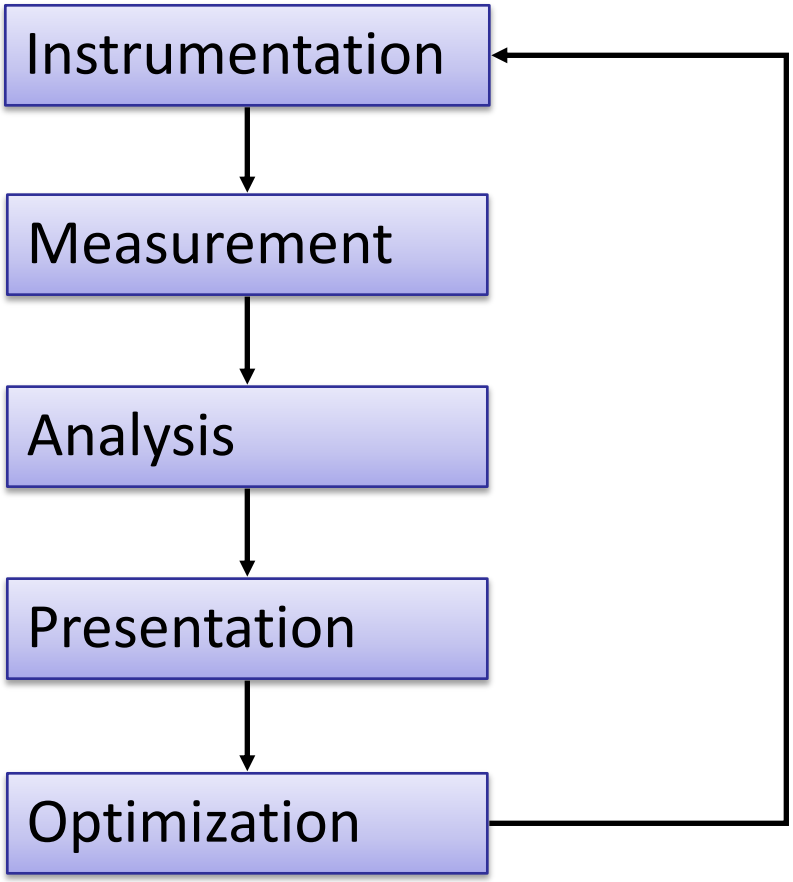

Instrumentation techniques

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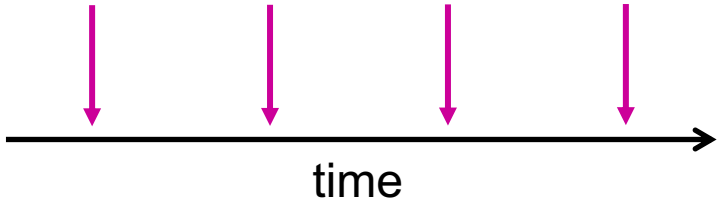
Direct instrumentation

- Measurement code is inserted at certain points in the program
- Example: function entry/exit, dispatch or receipt of messages

```
void foo(int i) {
  func_enter(" foo ");
    for (i = 0; i<end; ++i)
        do_something ( ) ;
  func_exit(" foo ");
}
```

Sampling

- Measurement performed only in certain intervals - usually implemented with timer interrupt



- Based on the assumption that a subset of a population being examined is representative for the whole population

Comparison

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	Direct instrumentation	Sampling
Advantage	Captures all instrumented events	Overhead can be easily controlled
Disadvantage	Overhead more difficult to control	Incomplete information, harder to access program state

Measurement

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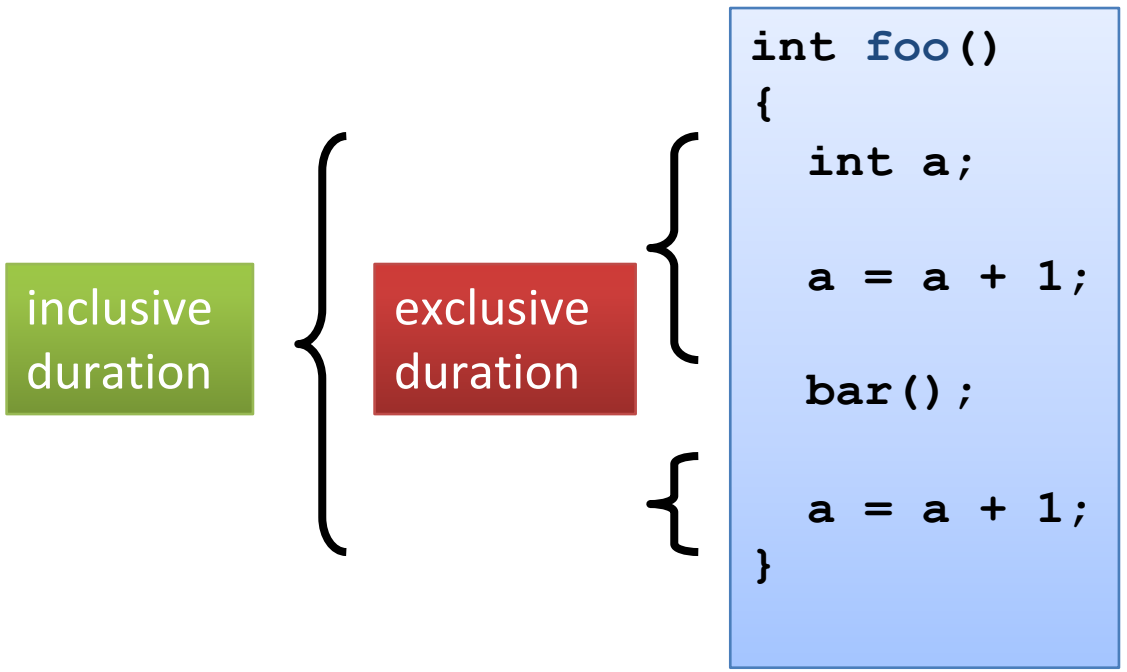
Typical performance data include counts and/or durations of

- Computation
- Communication
- Synchronization
- Input / output
- Hardware events (e.g., cache misses)



Critical issues

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Accuracy

- Perturbation – measurement alters program behavior
- Example: memory access pattern
- Intrusion overhead – measurement itself needs time and thus lowers performance
- Accuracy of timers, counters

Granularity

- How many measurements
- Pitfall: short but frequently executed functions
- How much information / work during each measurement?

Single-node performance

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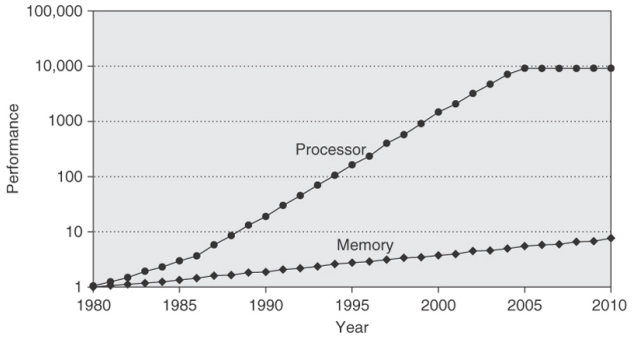
Huge gap between CPU and memory speed



Source: Hennessy, Patterson: Computer Architecture, 5th edition, Morgan Kaufmann

Internal operation of a microprocessor potentially complex

- Pipelining
- Out-of-order instruction issuing
- Branch prediction
- Non-blocking caches

Hardware counters

- Small set of registers that count events
- Events are signals related to the processor's internal function
- Original purpose – design verification and performance debugging for microprocessors
- Idea – use this information to analyze the performance behavior of an application as opposed to a CPU
- Can be measured with PAPI
  http://icl.utk.edu/papi/

Typical hardware counters

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Cycle count	
Instruction count	All instructions Floating point Integer Load / store
Branches	Taken / not taken Mispredictions
Pipeline stalls due to	Memory subsystem Resource conflicts
Cache	I/D cache misses for different levels Invalidations
TLB	Misses Invalidations

Performance profiling

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Mapping of aggregated information onto program and system entities

- Time
- Hardware counters
- Software counters
  - #function calls
  - #messages

- Functions
- Loops
- Call paths
- […]

- Processes
- Threads
- Nodes
- […]

Call-path profiling

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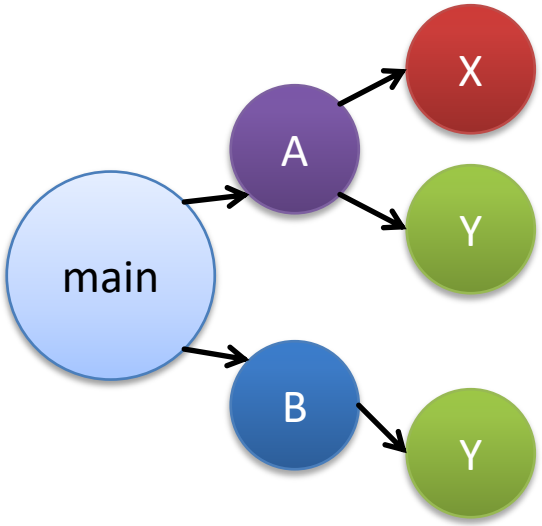
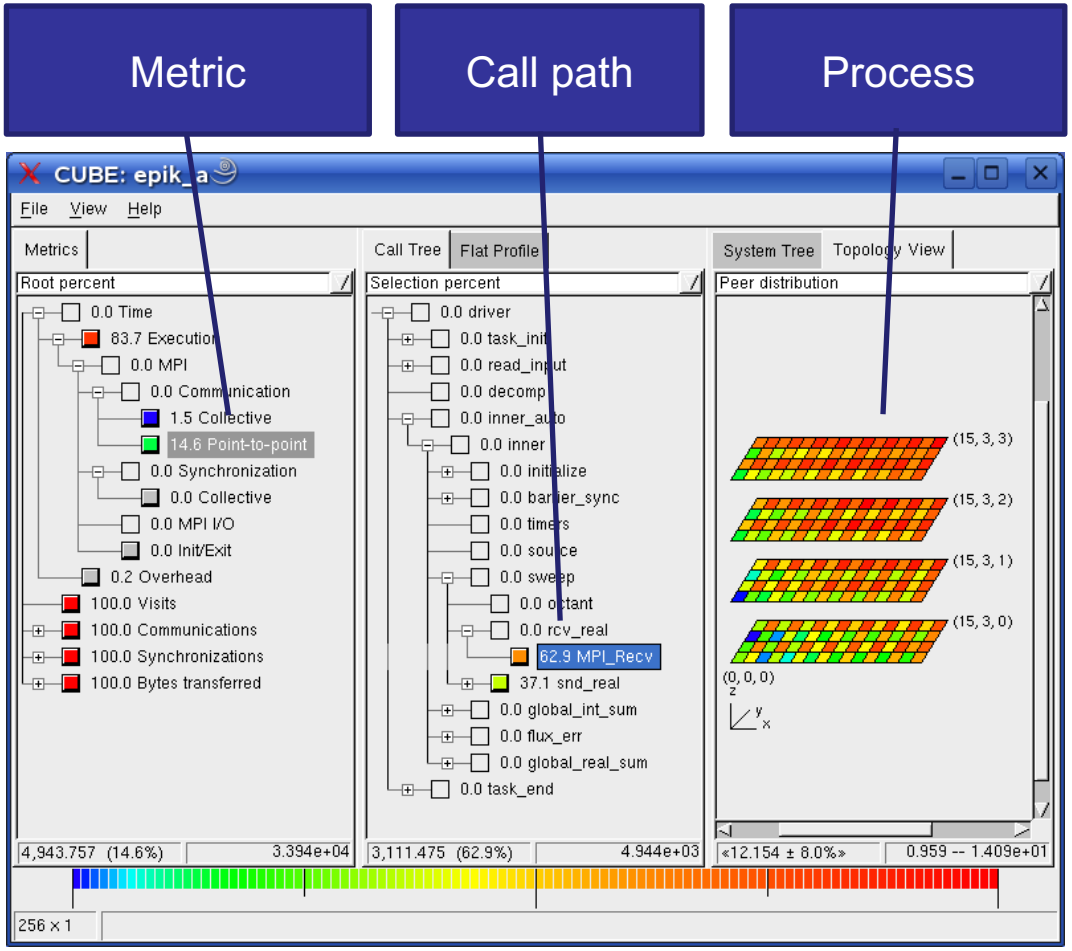
- Behavior of a function may depend on caller (i.e., parameters)
- Flat function profile often not sufficient
- How to determine call path at runtime?
  - Runtime stack walk
  - Maintain shadow stack
    - Requires tracking of function calls




```
main()
{
  A( );
  B( );
}


A( )        B( )
{           {
  X();        Y();
  Y();      }
}
```

Call-path profiling with Scalasca



www.scalasca.org

Event tracing

- Logging performance-critical events with timestamp
- Visualizing log in time-line diagram or analyzing it automatically

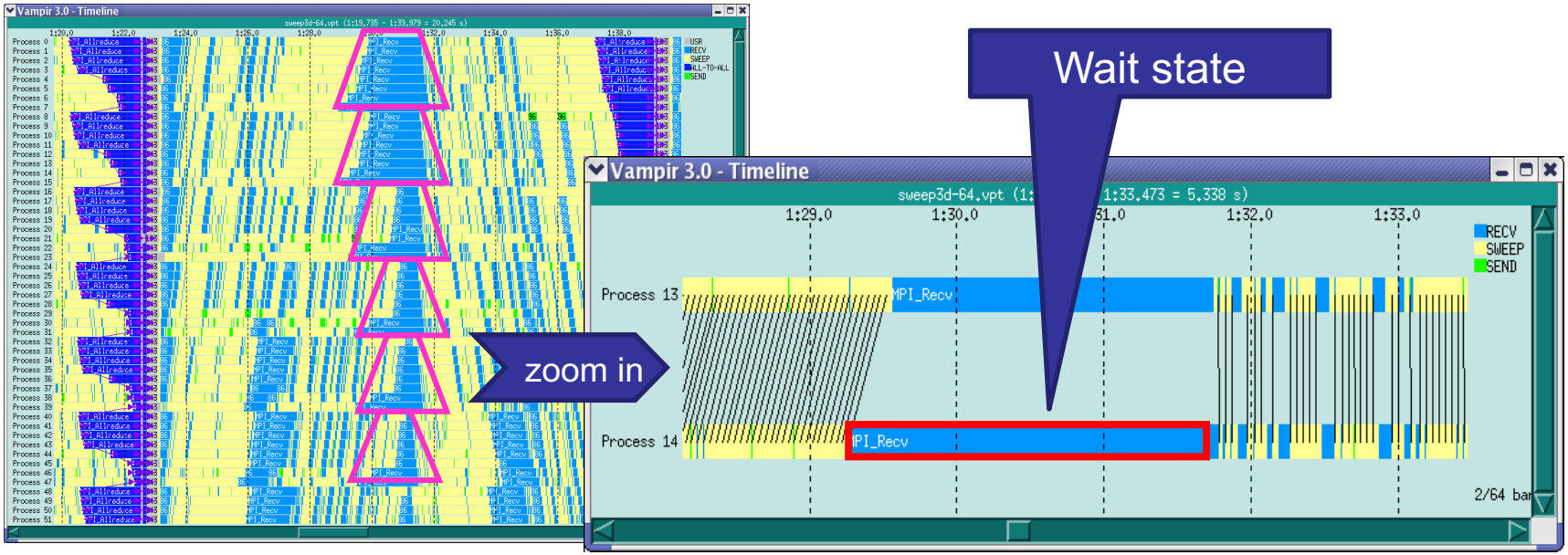
Screenshot of Vampir

Typical events

- Entering and leaving a function; sending and receiving a message

Interactive trace analysis with Vampir

Example: Sweep3D



https://www.vampir.eu

Automatic trace analysis with Scalasca
Example: Zeus-MP/2

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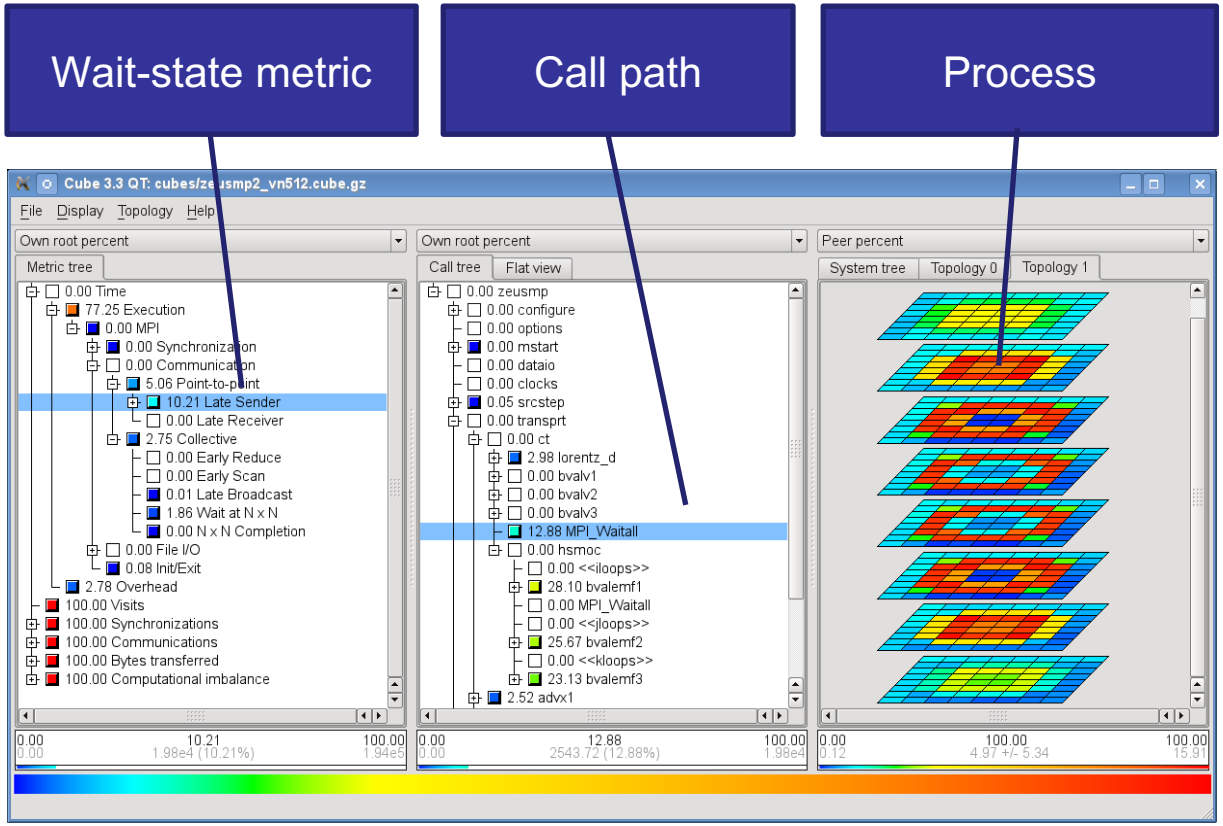

www.scalasca.org

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Origin of wait states
Example: Zeus-MP/2

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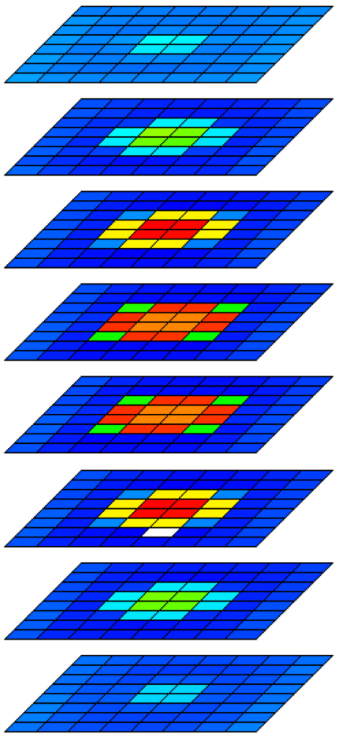
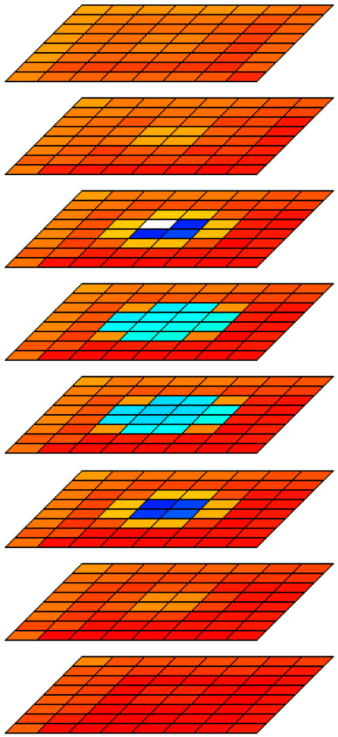
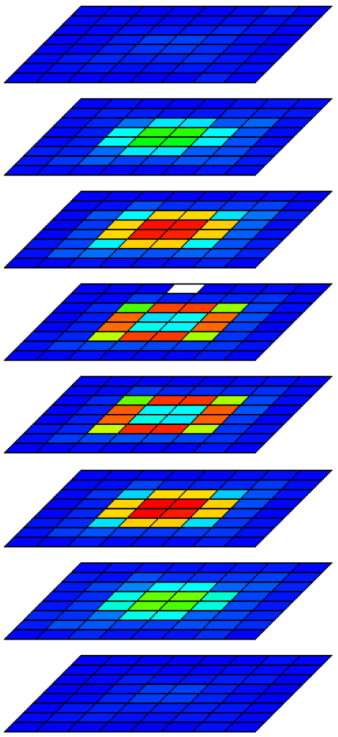


Computation



Waiting time



Delay costs

How to obtain profiles and traces?

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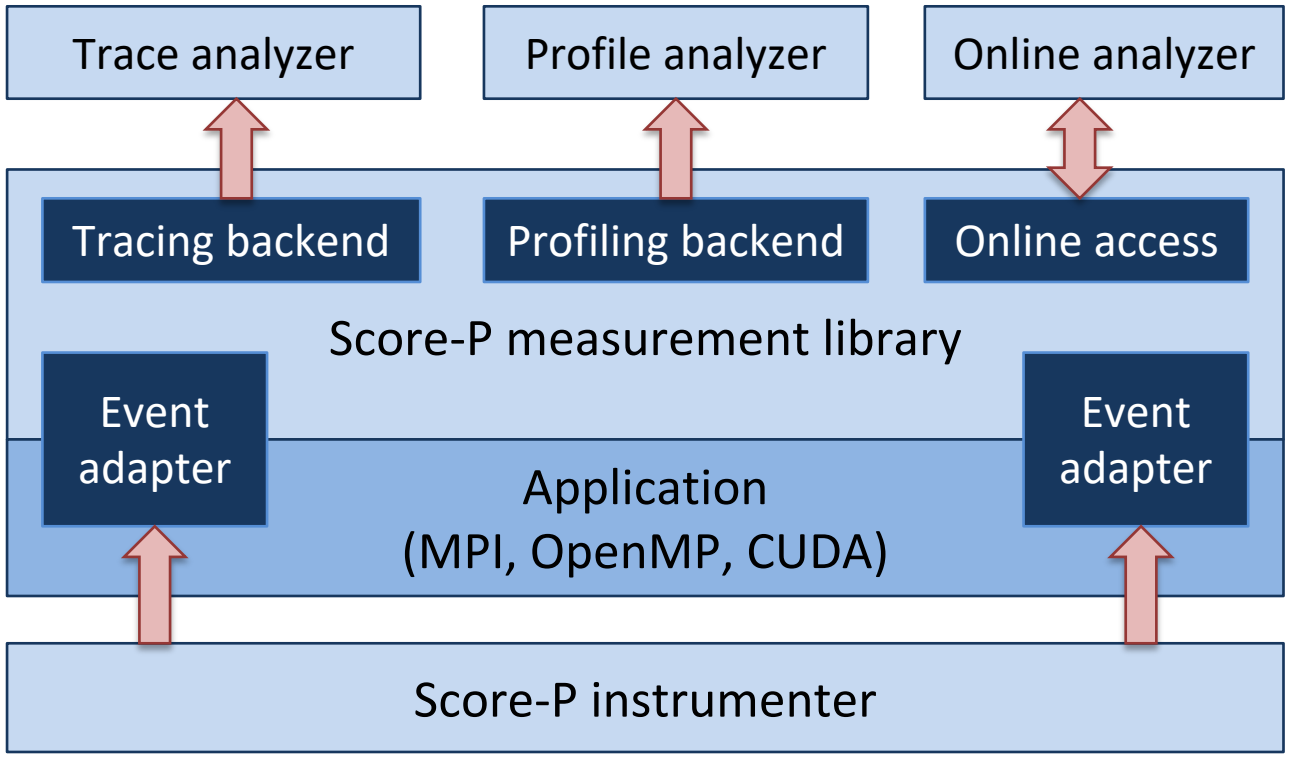
Score-P measurement system



http://www.vi-hps.org/projects/score-p/

Obstacle: trace size

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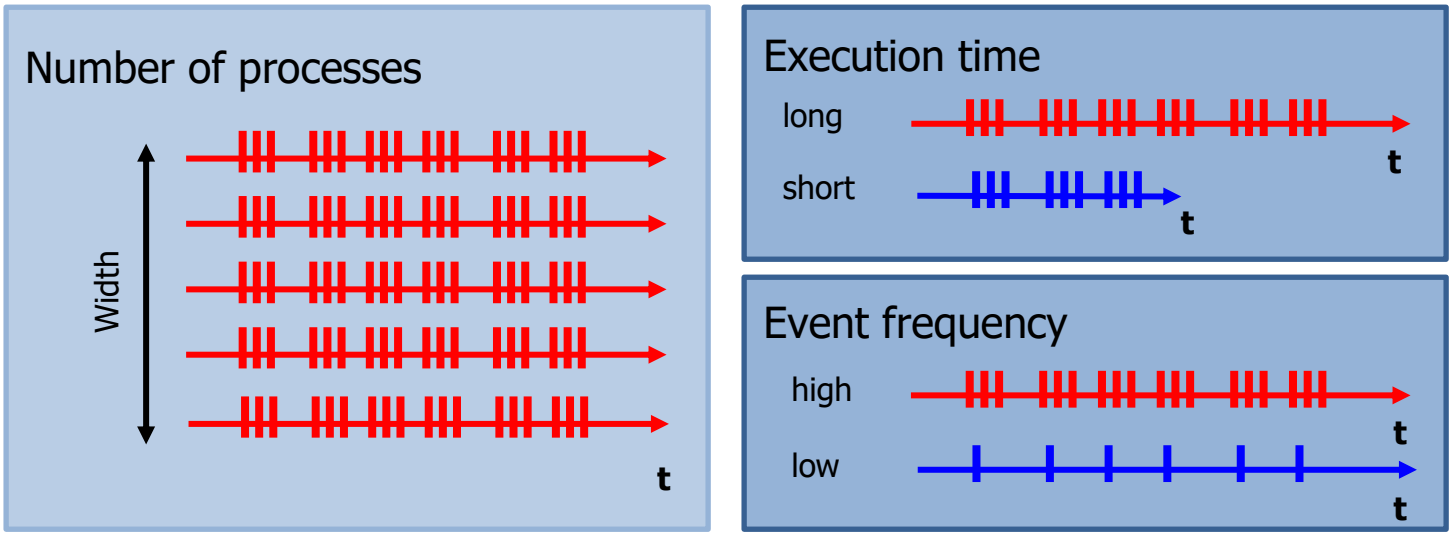
Problem – width and length of event trace



Latent scalability bugs

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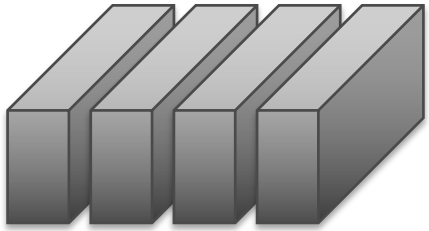
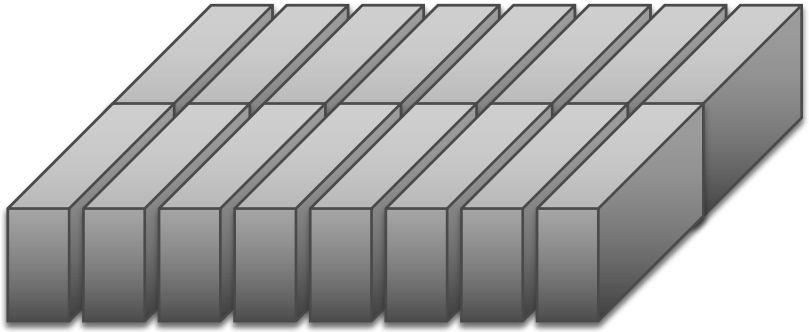
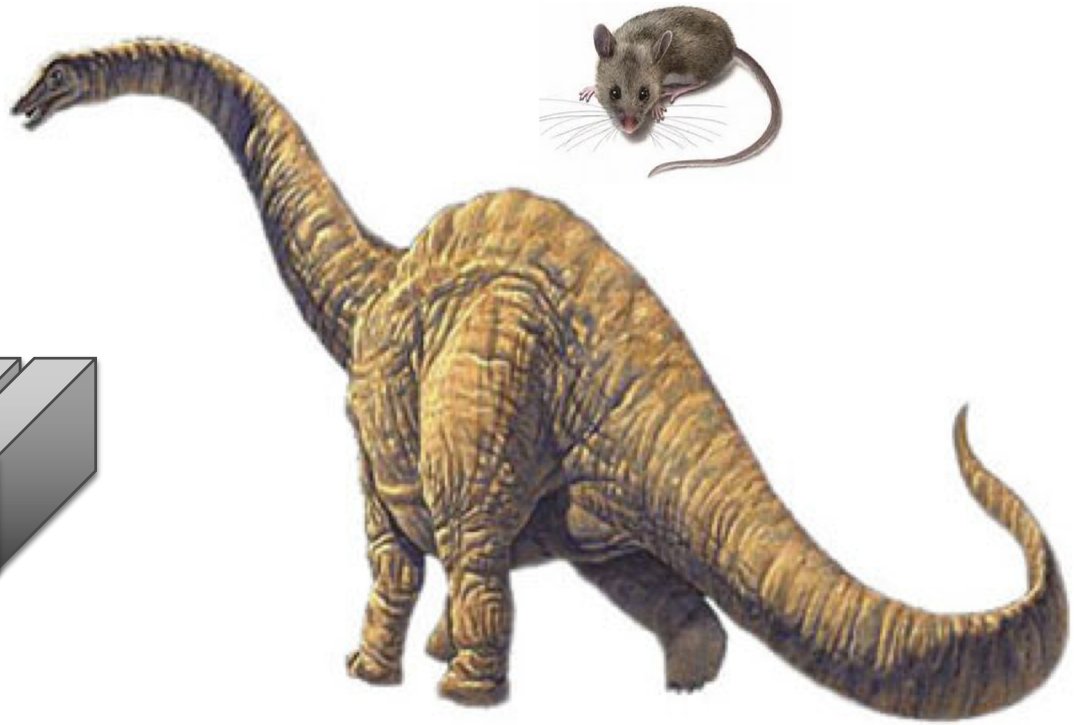
System size

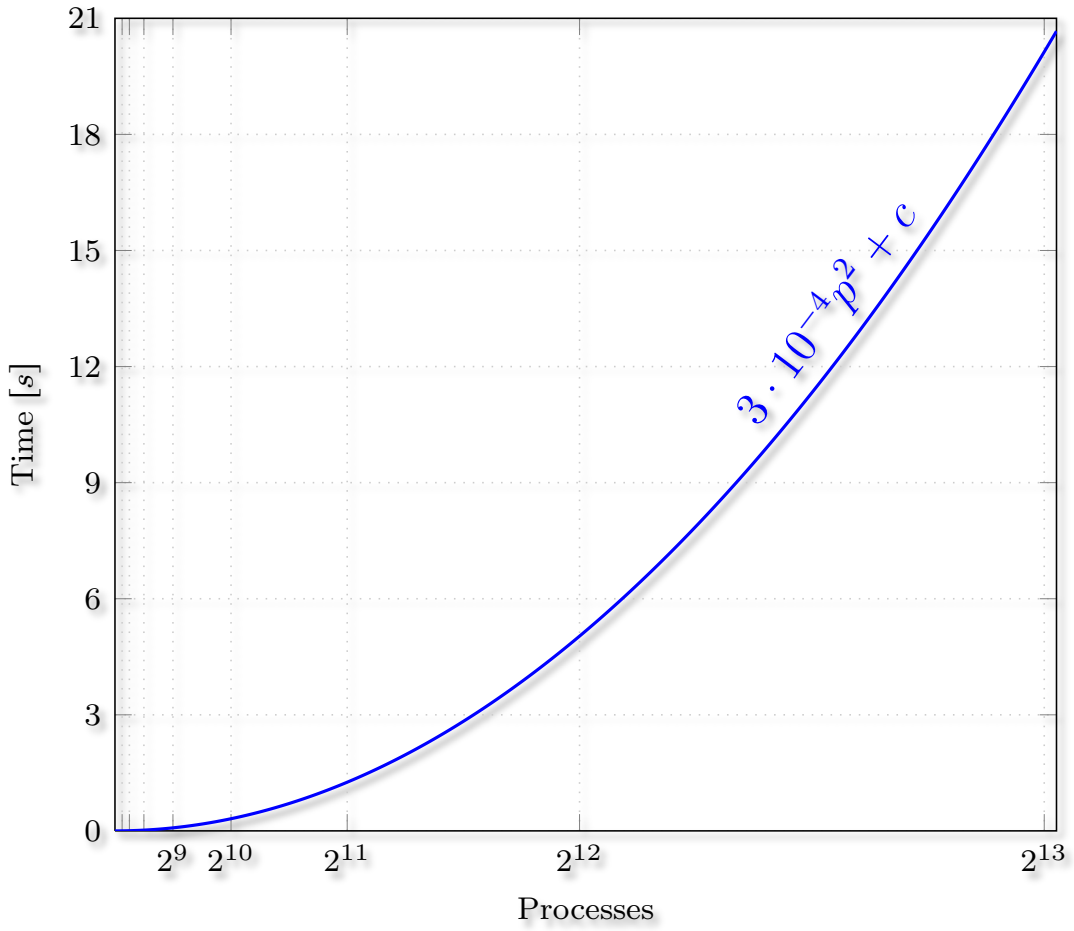




Execution time



Scalability model



Analytical scalability modeling

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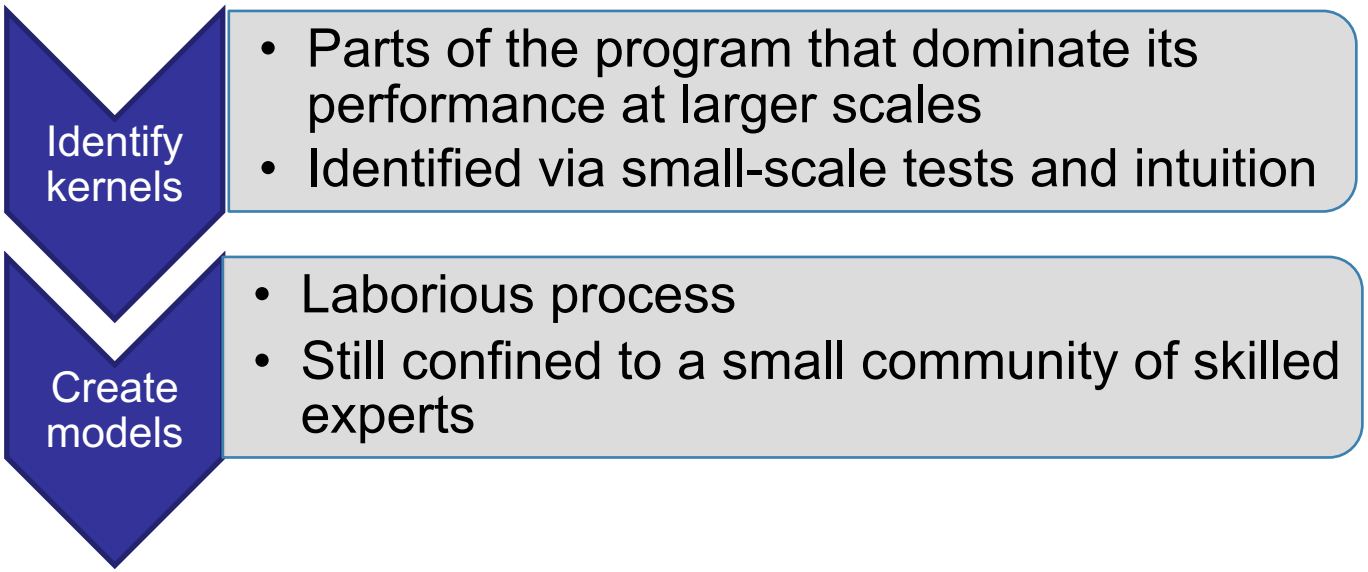
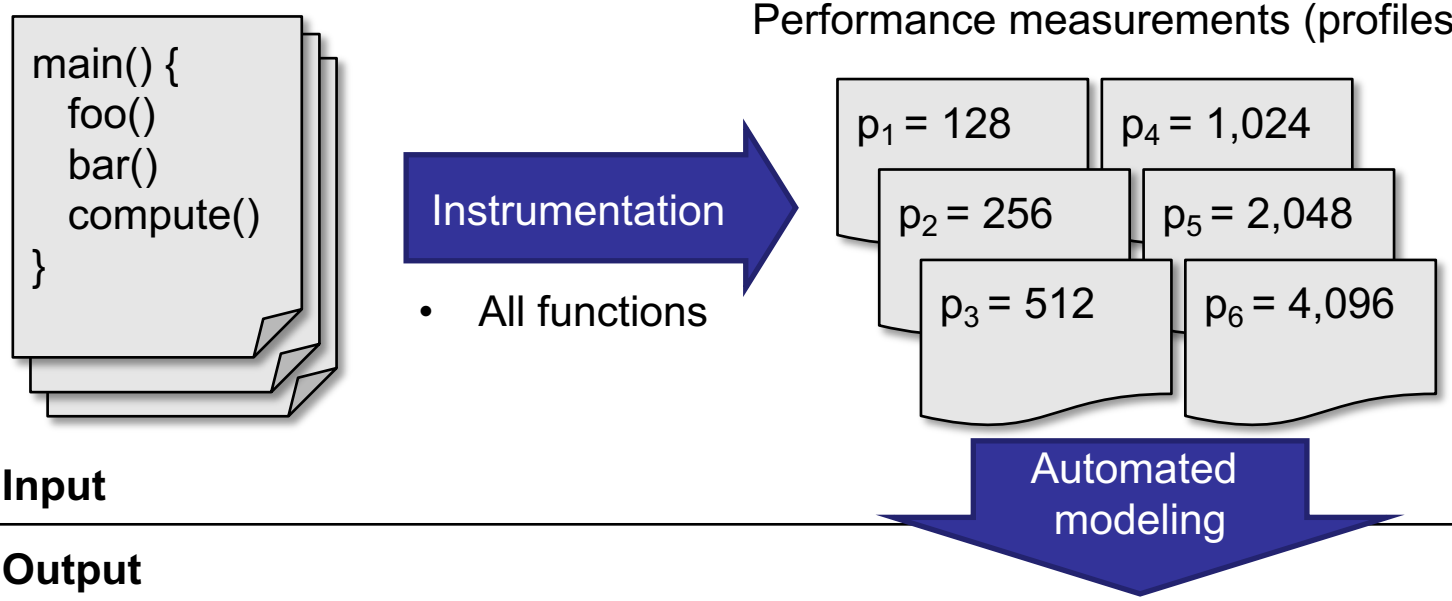


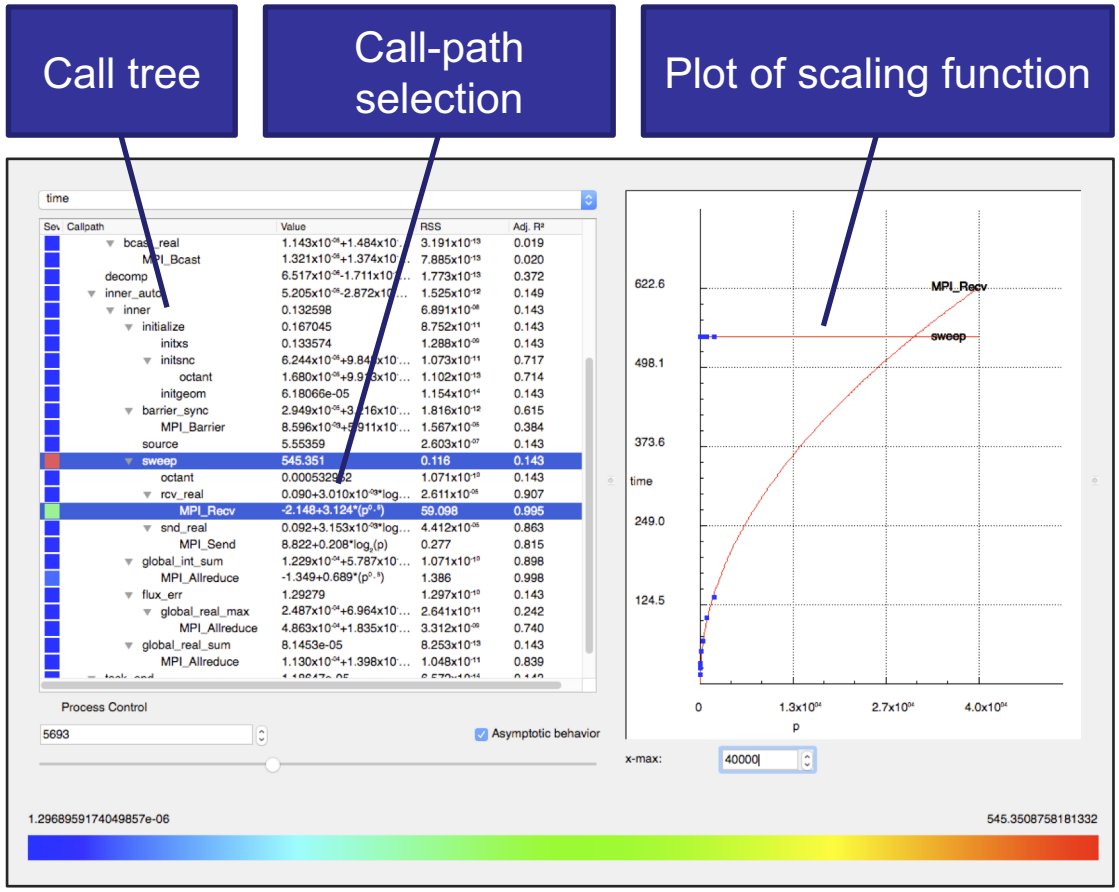
Disadvantages
- Time consuming
- Danger of overlooking unscalable code

Empirical scalability modeling



Function (with calling context)	Model [s] t = f(p)
sweep → MPI_Recv	$4.03\sqrt{p}$
sweep	582.19

Interactive scalability analysis with Extra-P

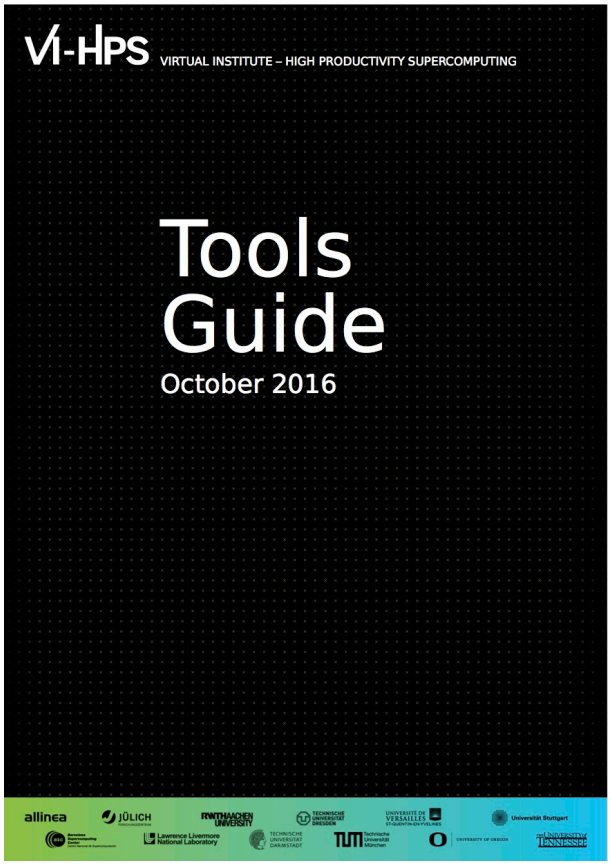


http://www.scalasca.org/software/extra-p

Virtual Institute – High Productivity Supercomputing

TECHNISCHE UNIVERSITÄT DARMSTADT

- Partnership for the development of advanced programming tools for HPC
  - http://www.vi-hps.org
- Activities
  - Tool development and integration
  - Training & support
  - Workshop series on extreme-scale programming tools (in conjunction with SC Conference)
- Publishes guide with information on available tools from VI-HPS



http://www.vi-hps.org/tools/