

Model-guided performance engineering of numerical kernels

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- Regular PRACE tutorials (two-day)
 - December @ LRZ Garching
 - July @ HLRS Stuttgart
- SC Conference tutorial (one-day)
 - Next: November 15, 2015, Austin, TX, USA
- SPPEXA collaboration activities
 - Next: September 29+30, 2015, TU Darmstadt
- ISC15 full-day workshop Performance Modeling: Methods and Applications, July 16, 2015, Frankfurt
- ... and probably some others





 $U(1)_Y \otimes SU(2)_L \otimes SU(3)_c$

"Black box" vs. "white box" models





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Others have said it better...

Overview of Performance Modeling

A Practical Approach to Performance Analysis and Modeling of Large-Scale Systems

Kevin J. Barker, Adolfy Hoisie, Darren J. Kerbyson

Fundamental & Computational Sciences Directorate

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Performance modeling	"Brand X"
Relies on understanding of tru application behavior	e Relies on pattern matching and curve fitting (extrapolation & interpolation)
White-box approach (application-centric)	Black-box approach (application-oblivious)
<i>Explains</i> performance; detail of explanation correlates with accuracy of prediction	of Predicts without providing insight or gauges of accuracy
Disagreements with measurements challenge assumptions and yield new insights	Disagreements with measurements merely showcase limitations of approach Pacific Northy
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Set up an (analytical) model for a given algorithm/kernel/solver/application on a given architecture

Compare with measurements to validate the model

(Hopefully) identify optimization opportunities and start over









Case study: Sparse Matrix Vector Multiplication on a multicore CPU

Part 1: Basics and observations



- Key ingredient in some matrix diagonalization algorithms
 - Lanczos, Davidson, Jacobi-Davidson
- Store only N_{nz} nonzero elements of matrix and RHS, LHS vectors with N_r (number of matrix rows) entries
- "Sparse": N_{nz} ~ N_r







"Compressed Row Storage"

- **val**[] stores all the nonzeros (length N_{nz})
- col_idx[] stores the column index of each nonzero (length N_{nz})
- row_ptr[] stores the starting index of each new row in val[] (length: N_r)





OpenMP-parallel loop kernel

```
!$OMP parallel do
do i = 1,N<sub>r</sub>
do j = row_ptr(i), row_ptr(i+1) - 1
c(i) = c(i) + val(j) * b(col_idx(j))
enddo
enddo
!$OMP end parallel do
```

Usually many spMVMs required to solve a problem

Performance characteristics on Intel Sandy Bridge CPU



- Performance does not scale across the cores on a CPU chip
- Performance seems to depend on the matrix





"White box" performance modeling on the chip level: Roofline



D. Callahan et al.: Estimating interlock and improving balance for pipelined architectures. Journal for Parallel and Distributed Computing 5(4), 334 (1988). DOI: 10.1016/0743-7315(88)90002-0

W. Schönauer: <u>Scientific Supercomputing: Architecture and Use of Shared and Distributed</u> <u>Memory Parallel Computers</u>. Self-edition (2000)

S. Williams: <u>Auto-tuning Performance on Multicore Computers</u>. UCB Technical Report No. UCB/EECS-2008-164. PhD thesis (2008)

Prelude: Modeling customer dispatch in a bank







How fast can tasks be processed? **P** [tasks/sec]

The bottleneck is either

- The service desks (max. tasks/sec):
- The revolving door (max. customers/sec):

 P_{\max} $I \cdot b_S$





- P_{max} = Applicable peak performance of a loop, assuming that data comes from the level 1 cache (this is not necessarily P_{peak})
 → e.g., P_{max} = 176 GFlop/s
- *I* = Computational intensity ("work" per byte transferred) over the slowest data path utilized (code balance B_C = *I*⁻¹)
 → e.g., *I* = 0.167 Flop/Byte → B_C = 6 Byte/Flop
- 3. $b_s = \text{Applicable peak bandwidth of the slowest data path utilized}$ $\rightarrow \text{ e.g., } b_s = 56 \text{ GByte/s}$



Example: Dense matrix-vector multiplication in double precision on an Intel Haswell processor



do i=1,Ndo j=1,N $c(i)=c(i)+A(j,i)*b(j) \Rightarrow$ enddo enddo do i=1,N tmp = c(i) do j=1,N tmp = tmp + A(j,i)* b(j) enddo c(i) = tmp enddo enddoenddo

- Assume N ≈ 5000
- Applicable peak performance?
- Relevant data path?
- Computational Intensity?

- \rightarrow does not fit in cache
- → half peak (2 LD, 1 ADD, 1 MULT)
- \rightarrow main memory
- → 2 flops / 8 bytes = 0.25 F/B (b() comes from cache)

Example: Dense matrix-vector multiplication in double precision on an Intel Haswell processor



- Haswell CPU hardware characteristics
 - 14 cores
 - 2.5 MByte of cache per core
 - 8 ADDs + 8 MULTs per core per clock cycle
 - Clock speed = 2.3 GHz
 - $\rightarrow P_{\text{max}} = \frac{1}{2} P_{\text{peak}} = \frac{1}{2} \times 14 \times 16 \times 2.3 \text{ GFlop/s} = 258 \text{ GFlop/s}$
 - Max. memory bandwidth (measured) b_S = 56 GByte/s
- Roofline model: $P = \min\left(258 \frac{\text{GFlop}}{\text{s}}, 0.25 \frac{\text{Flop}}{\text{Byte}} \cdot 56 \frac{\text{GByte}}{\text{s}}\right) = 14 \text{ GFlop/s}$
 - \rightarrow Code is memory bound
 - → 2.7% of peak performance!
- What can you do to improve it?

If the code runs at 14 Gflop/s, nothing.



- There is a clear concept of "work" vs. "traffic"
 - "work" = flops, updates, iterations...
 - "traffic" = required data to do "work"
- No latency effects → perfect streaming mode
- One data transfer bottleneck is modeled only; all others are assumed to be infinitely fast

Data transfer and core execution overlap perfectly!

- This is the main problem in situations where Roofline does not work!
- Remedy: Execution-Cache-Memory (ECM) model

H. Stengel, J. Treibig, G. Hager, and G. Wellein: *Quantifying performance bottlenecks of stencil computations using the Execution-Cache-Memory model*. Proc. ICS'15, DOI: 10.1145/2751205.2751240, Preprint: <u>arXiv:1410.5010</u>

G. Hager, J. Treibig, J. Habich, and G. Wellein: *Exploring performance and power properties of modern multicore chips via simple machine models*. Concurrency and Computation: Practice and Experience (2013), <u>DOI: 10.1002/cpe.3180</u>. Preprint: <u>arXiv:1208.2908</u>



Case study: Sparse Matrix Vector Multiplication on a multicore CPU

Part 2: Modeling

Example: SpMVM node performance model





- "Expected" performance = b_S x l_{CRS}
- Determine α by measuring performance and actual memory traffic
 - Maximum memory BW may not be achieved with spMVM

Determine RHS traffic



$$I_{CRS}^{DP} = \frac{2}{8+4+8\alpha+16/N_{nzr}} \frac{\text{flops}}{\text{byte}} = \frac{N_{nz} \cdot 2 \text{ flops}}{V_{meas}}$$

 V_{meas} is the measured overall memory data traffic (using, e.g., likwidperfctr)

• Solve for
$$\alpha$$
: $\alpha = \frac{1}{4} \left(\frac{V_{meas}}{N_{nz} \cdot 2 \text{ bytes}} - 6 - \frac{8}{N_{nzr}} \right)$

 Example: kkt_power matrix from the UoF collection on one Intel SNB socket

•
$$N_{nz} = 14.6 \cdot 10^6$$
, $N_{nzr} = 7.1$

▪ *V_{meas}* ≈ 258 MB

$$\rightarrow \alpha = 0.43, \, \alpha N_{nzr} = 3.1$$

- → RHS is loaded 3.1 times from memory
- and:

$$\frac{I_{CRS}^{DP}(1/N_{nzr})}{I_{CRS}^{DP}(\alpha)} = 1.15$$

15% extra traffic → optimization potential!



Now back to the start...





Now what next?

- Matrix reordering may improve balance → faster code
- Check other performance-limiting factors (load imbalance, non-streaming)
- Saturation effect cannot be explained by Roofline (in a satisfying way)

"DLR1" (A. Basermann, DLR)

Adjoint problem computation (turbulent transonic flow over a wing) with the TAU CFD system of the German Aerospace Center (DLR) Avg. non-zeros/row ~150

"sAMG" (K. Stüben, FhG-SCAI) Matrix from FhG's adaptive multigrid code sAMG for the irregular discretization of a Poisson problem on a car geometry.

Avg. non-zeros/row ~ 7

- Conclusion from Roofline analysis
 - The roofline model can only deliver an optimistic absolute upper limit for spMVM due to the RHS traffic uncertainties
 - We have "turned the model around" and measured the actual memory traffic to determine the RHS overhead
 - Result indicates:
 - 1. how much actual traffic the RHS generates
 - 2. how efficient the RHS access is (compare BW with max. BW)
 - 3. how much optimization potential we have with matrix reordering

Consequence: Modeling is not always 100% predictive. It's all about *learning more* about performance properties!

Typical code optimizations in the Roofline Model

1. Hit the BW bottleneck by good serial code

(e.g., Perl \rightarrow Fortran)

- 2. Increase intensity to make better use of BW bottleneck (e.g., loop blocking [see later])
- 3. Increase intensity and go from memory-bound to core-bound (e.g., temporal blocking)
- 4. Hit the core bottleneck by good serial code (e.g., -fno-alias [see later])
- Shift P_{max} by accessing additional hardware features or using a different algorithm/implementation (e.g., scalar → SIMD)

Best practices for benchmarking and optimization

Motivation:

- Understand observed performance
- Learn about code characteristics and machine capabilities
- Deliberately decide on optimizations

Process:

- 1. Define relevant test cases (similar to production runs)
- 2. Establish a sensible performance metric (work/time)
- 3. Acquire a runtime profile (where does the time go?)
- 4. Identify "hot" loop kernels (hopefully there are any!)
- 5. Try to build a simple performance model
- 6. Optimize the kernel if possible

iterate

Preparation

- Care for reliable timing (minimum time which can be measured?)
- Document code generation (flags, compiler version)
- Get access to an exclusive system
- System state (clock speed, turbo mode, memory, caches)
- Consider automating runs with a script (shell, python, perl)

Doing

- Affinity control
- Check: Is the result reasonable? (300 PFlop/s are not)
- Is result deterministic and reproducible? (if not, search for reasons)
- Statistics: Mean, Best?
- Basic variants to check
 - Thread count, affinity, working set size

Thank you.

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hpcADD

