

Performance Tuning of Scientific **Codes with the Roofline Model**

BORATORY

8:30am 8:35am 9:15am 10:00am 10:30am 11:15am 11:55pm

Welcome/Introductions **Roofline Introduction** Roofline on GPU-accelerated Systems break **Roofline on CPU-based Systems HPC** Application Studies closing remarks / Q&A

all Samuel Williams Charlene Yang

Jack Deslippe all



Samuel Williams



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Introduction to the Roofline Model

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Background





Why Use Performance Models or Tools?

- Identify performance bottlenecks
- Motivate software optimizations
- **Determine when we're done optimizing**
 - Assess performance relative to machine capabilities ullet
 - Motivate need for algorithmic changes ullet
- Predict performance on future machines / architectures
 - Sets realistic expectations on performance for future procurements
 - Used for HW/SW Co-Design to ensure future architectures are well-suited for the ulletcomputational needs of today's applications.





- Many different components can contribute to kernel run time.
- Some are application-specific, and some architecture-specific.

#FP operations Flop/s Cache data movement Cache GB/s DRAM data movement DRAM GB/s PCIe data movement PCIe bandwidth Depth OMP Overhead MPI Message Size Network Bandwidth MPI Send:Wait ratio Network Gap #MPI Wait's Network Latency

ne. cific.



Can't think about all these terms all the time for every application...

Computational Complexity #FP operations Flop/s Cache data movement Cache GB/s DRAM data movement DRAM GB/s PCIe data movement PCIe bandwidth Depth OMP Overhead MPI Message Size Network Bandwidth MPI Send: Wait ratio Network Gap #MPI Wait's Network Latency



Because there are so many components, performance models often conceptualize the system as being dominated by one or more of these components.

> **#FP operations** Flop/s Cache data movement Cache GB/s DRAM data movement DRAM GB/s PCIe data movement PCIe bandwidth Depth OMP Overhead MPI Message Size Network Bandwidth MPI Send: Wait ratio Network Gap LogP #MPI Wait's Network Latency

Culler, et al, "LogP: a practical model of parallel computation", CACM. 1996.



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9

the LogP model - one step closer towards a realistic model for parallel computation", SPAA, 1995.





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> Roofline **#FP operations** Flop/s Model Cache data movement Cache GB/s DRAM data movement DRAM GB/s PCIe data movement PCIe bandwidth Depth OMP Overhead MPI Message Size Network Bandwidth MPI Send: Wait ratio Network Gap #MPI Wait's Network Latency

Williams et al, "Roofline: An Insightful Visual Performance Model For Multicore Architectures", CACM, 2009.



Performance Models / Simulators

- Historically, many performance models and simulators tracked time to predict performance (i.e. counting cycles)
- The last two decades saw a number of latency-hiding techniques...
 - Out-of-order execution (hardware discovers parallelism to hide latency)
 - HW stream prefetching (hardware speculatively loads data) ۲
 - Massive thread parallelism (independent threads satisfy the latency-bandwidth product) ullet
- ... resulted in a shift from a latency-limited computing regime to a throughput-limited computing regime





Roofline Model

- **Roofline Model** is a throughput-oriented performance model...
 - Tracks rates not times
 - Augmented with Little's Law (concurrency = latency*bandwidth)
 - Independent of ISA and architecture (applies ulletto CPUs, GPUs, Google TPUs¹, etc...)

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•	Facebook	0.1-1.0 flops p	er byte Typically < 2

https://crd.lbl.gov/departments/computer-science/PAR/research/roofline







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Roofline Model: Arithmetic Intensity and Bandwidth



- One could hope to always attain peak performance (Flop/s)
- However, finite reuse and bandwidth limit performance.
- Assuming perfect overlap of communication and computation...



#FP ops / Peak GFlop/s #Bytes / Peak GB/s Time = max



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Peak GFlop/s (#FP ops / #Bytes) * Peak GB/s #FP ops Time



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Note, Arithmetic Intensity (AI) = Flops / Bytes (as presented to DRAM)



- Plot Roofline bound using Arithmetic Intensity as the x-axis
- Log-log scale makes it easy to doodle, extrapolate performance along Moore's Law, etc...
- Kernels with AI less than machine balance are ultimately DRAM bound (we'll refine this later...)





- Typical machine balance is 5-10 flops per byte...
 - 40-80 flops per double to exploit compute capability
 - Artifact of technology and money •
 - Unlikely to improve ٠
- Consider STREAM Triad...

#pragma omp parallel for for(i=0;i<N;i++){</pre> Z[i] = X[i] + alpha*Y[i];

- 2 flops per iteration ٠
- Transfer 24 bytes per iteration (read X[i], Y[i], write Z[i]) ٠
- AI = 0.083 flops per byte == Memory bound ٠





- Conversely, 7-point constant coefficient stencil...
 - 7 flops •
 - 8 memory references (7 reads, 1 store) per point •
 - AI = 0.11 flops per byte (L1) •

```
#pragma omp parallel for
for(k=1;k<dim+1;k++){</pre>
for(j=1;j<dim+1;j++){</pre>
for(i=1;i<dim+1;i++){</pre>
 new[k][j][i] = -6.0*old[k ][j ][i
                     + old[k ][j ][i-1]
                     + old[k ][j ][i+1]
                     + old[k ][j-1][i
                     + old[k ][j+1][i
                     + old[k-1][j
                     + old[k+1][j ][i
}}}
```







DRAM Bandwidth (GB/s)



- Conversely, 7-point constant coefficient stencil...
 - 7 flops •
 - 8 memory references (7 reads, 1 store) per point •
 - Cache can filter all but 1 read and 1 write per point
 - AI = 0.44 flops per byte •





Cache Bandwidth



Conversely, 7-point constant coefficient stencil...

- 7 flops
- 8 memory references (7 reads, 1 store) per point •
- Cache can filter all but 1 read and 1 write per point ٠
- AI = 0.44 flops per byte == memory bound, •

but 5x the flop rate









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Refining Roofline: **Memory Hierarchy**







Data Movement

L1 GB

L2 GB

MCDRAM GB

DRAM GB



- Processors have multiple levels of memory/cache
 - Registers
 - L1, L2, L3 cache
 - MCDRAM/HBM (KNL/GPU device memory)
 - DDR (main memory)
 - NVRAM (non-volatile memory)
- Applications have locality in each level
 - Unique data movements imply unique Al's
 - Moreover, each level will have a unique bandwidth



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Arithmetic Intensity

<u>GFlop's</u> L1 GB <u>GFlop's</u> L2 GB <u>GFlop's</u> MCDRAM GB

> GFlop's DRAM GB



- Construct superposition of Rooflines...
 - Measure bandwidth
 - Measure AI for each level of memory
 - Although an loop nest may have multiple ulletAl's and multiple bounds (flops, L1, L2, ... **DRAM**)...
 - ... performance is bound by the • minimum





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NUMA Effects

- Cori's Haswell nodes are built from 2 Xeon processors (sockets)
 - Memory attached to each socket (fast)
 - Interconnect that allows remote memory access (slow == NUMA)
 - Improper memory allocation can result in more than a 2x performance penalty









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Refining Roofline: **In-core Effects**





In-Core Parallelism

- We have assumed one can attain peak flops with high locality.
- In reality, we must …
 - Vectorize loops (16 flops per instruction)
 - Use special instructions (e.g. FMA)
 - Ensure FP instructions dominate the instruction mix
 - Hide FPU latency (unrolling, out-of-order execution)
 - Use all cores & sockets
- Without these, ...
 - Peak performance is not attainable
 - Some kernels can transition from memory-bound to compute-bound ullet





Data Parallelism (e.g. SIMD)

- Most processors exploit some form of SIMD or vectors.
 - KNL uses 512b vectors (8x64b)
 - GPUs use 32-thread warps (32x64b) •
- In reality, applications are a mix of scalar and vector instructions.
 - **Performance is a weighted average** ٠ between SIMD and no SIMD





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- In reality, applications are a mix of scalar and vector instructions.
 - Performance is a weighted average between SIMD and no SIMD
 - There is an implicit ceiling based on this weighted average

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		Full v
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A		
	Arithmetic Inten	si

vectorization

Partial vectorization vectorization

Memory-bound codes can become compute-bound



Return of CISC

 Modern CPUs and GPUs are increasingly reliant on special (fused) instructions that perform multiple operations.

0	FMA (Fused Multiply Add):	z=a*x+y	z,x,y are vectors or scal
0	4FMA (quad FMA):	z=A*x+z	A is a FP32 matrix; x,z a
0	WMMA (Tensor Core):	Z=AB+C	Z,A,B,C are FP16 matri

n.b., this is orthogonal to SIMD where the the same operation(s) is applied to a vector of operands.

Performance is now a weighted average of scalar, vector, FMA, and WMMA operations.

lars are vectors ICes


Return of CISC

- Total lack of FMA reduces performance by 2x on KNL.
 (4x on Haswell)
- In reality, applications are a mix of FMA, FAdd, and FMul.
 - Performance is a weighted average
 - There is an implicit ceiling based on this weighted average





Return of CISC

- On Volta, Tensor cores can provide 100TFLOPs of FP16 performance (vs. 7.5 TFLOPS for DP FMA)
- Observe, machine balance has now grown to ...
 - 100 TFLOP/s / 800 GB/s
 - = 125 FP16 per byte !!







DP Add Peak

DP FMA Peak

Tensor Peak

Floating-Point Divides

- Although many processors support a Floating-point divide instruction, most implement divides through a sequence of FP instructions
 - rcp (reciprocal estimate to k bits) Ο
 - Newton-Raphson iterations (mul+FMA) to recover full precision
- All of these instructions can be pipelined and/or executed out of order

FP Divides increase arithmetic intensity and increase raw Flop rates.



Floating-Point Divides

- #FP operations deduced from source code can be an underestimate...
 - FP Divides require 10+ instructions on KNL and GPUs.
 - These must be included in both AI and Flop/s to affect proper Roofline analysis
 - As a result, Al and performance both increase and one can be compute-bound





- Superscalar processors have finite instruction fetch/decode/issue bandwidth (e.g. 4 instructions per cycle)
- Moreover, the number of FP units dictates the FP issue rate required to hit peak (e.g. 2 vector instructions per cycle)
- Ratio of these two rates is the FP instruction fraction required to hit peak





- Haswell CPU
 - 4-issue superscalar ٠
 - Only 2 FP data paths ullet
 - Requires 50% of the instructions to be FP to get peak performance







Haswell CPU

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Haswell CPU

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- Only 2 FP data paths
- Requires 50% of the instructions to be FP to get peak performance
- Conversely, on KNL...
 - 2-issue superscalar
 - 2 FP data paths
 - Requires 100% of the instructions to be FP to get peak performance
 - Codes that would have been memorybound are now decode/issue-bound.







- On Volta, each SM is partitioned among 4 warp schedulers
- Each warp scheduler can dispatch 32 threads per cycle
- However, it can only execute 8 DP FP instructions per cycle.
- i.e. there is plenty of excess instruction issue bandwidth available for non-FP instructions.









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Refining Roofline: Locality Effects





 Naively, we can bound AI using only compulsory cache misses







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- However, write allocate caches can lower Al







- Naively, we can bound AI using only compulsory cache misses
- However, write allocate caches can lower Al
- Cache capacity misses can have a huge penalty



$AI = \frac{\#Flop's}{Compulsory Misses + Write Allocates + Capacity Misses}$



- Naively, we can bound AI using only compulsory cache misses
- However, write allocate caches can lower Al
- Cache capacity misses can have a huge penalty
- Compute bound became memory bound



$AI = \frac{\#Flop's}{Compulsory Misses + Write Allocates + Capacity Misses}$



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Overview of Roofine Methodology



Machine Characterization

• "Theoretical Performance" numbers can be highly optimistic...

- Pin BW vs. sustained bandwidth
- TurboMode at low concurrency
- Underclocking for AVX
- Compiler failing on high-AI loops.

Take marketing numbers with a grain of salt



Machine Characterization

- To create a Roofline model, we must benchmark...
 - **Sustained Flops** 0
 - Double/single/half precision
 - With and without FMA (e.g. compiler flag)
 - With and without SIMD (e.g. compiler flag)
 - Sustained Bandwidth 0
 - Measure between each level of memory/cache
 - Iterate on working sets of various sizes and identify plateaus
 - Identify bandwidth asymmetry (read:write ratio)
- Benchmark must run long enough to observe effects of power throttling



Measuring Application Al and Performance

- To characterize execution with Roofline we need...
 - Time \bigcirc
 - **Flops** (=> flop's / time) Ο
 - **Data movement** between each level of memory (=> Flop's / GB's)
- We can look at the full application...
 - Coarse grained, 30-min average Ο
 - Misses many details and bottlenecks Ο
- or we can look at individual loop nests...
 - Requires auto-instrumentation on a loop by loop basis Ο
 - Moreover, we should probably differentiate data movement or flops on a core-by-core basis. Ο





How Do We Count Flop's?

Manual Counting

- Go thru each loop nest and count the number of FP operations
- Works best for deterministic loop bounds
- or parameterize by the number of iterations (recorded at run time)
- X Not scalable

Perf. Counters

- Read counter before/after
- ✓ More Accurate
- Low overhead (<%) == can run full MPI applications
- ✓ Can detect load imbalance
- X Requires privileged access
- X Requires manual instrumentation (+overhead) or full-app characterization
- **X** Broken counters = garbage
- X May not differentiate FMADD from FADD
- X No insight into special pipelines 57

Binary Instrumentation

- Automated inspection of assembly at run time
- ✓ Most Accurate
- ✓ FMA-, VL-, and mask-aware
- Can count instructions by class/type
- Can detect load imbalance
- ✓ Can include effects from non-FP instructions
- ✓ Automated application to multiple loop nests
- X >10x overhead (short runs /
 - reduced concurrency)



How Do We Measure Data Movement?

Manual Counting

- Go thru each loop nest and estimate how many bytes will be moved
- Use a mental model of caches
- ✓ Works best for simple loops that stream from DRAM (stencils, FFTs, spare, ...)
- **X** N/A for complex caches
- Not scalable

Perf. Counters

- Read counter before/after
- \checkmark Applies to full hierarchy (L2, DRAM,
- ✓ Much more Accurate
- Low overhead (<%) == can run full MPI applications
- ✓ Can detect load imbalance
- Requires privileged access
- **X** Requires manual instrumentation (+overhead) or full-app characterization

Cache Simulation

- Build a full cache simulator driven by memory addresses
- ✓ Applies to full hierarchy and multicore
- Can detect load imbalance
- ✓ Automated application to multiple loop nests
- **X** Ignores prefetchers
- X >10x overhead (short runs / reduced concurrency)







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Roofline-Driven Optimization





- Imagine a mix of loop nests
- Flop/s alone may not be useful in deciding which to optimize first





• We can sort kernels by AI ...





- We can sort kernels by AI …
- ... and compare performance relative to machine capabilities





- Kernels near the roofline are making good use of computational resources
 - kernels can have low performance 0 (Gflop/s), but make good use of a machine
 - kernels can have high performance Ο (Gflop/s), but make poor use of a machine





Tracking Progress Towards Optimality

- One can conduct a Roofline optimization after every optimization (or once per quarter)
 - Tracks progress towards optimality Ο
 - Allows one to quantitatively speak to Ο ultimate performance / KPPs
 - Can be used as a motivator for new \bigcirc algorithms.





Peak Flop/s **D** Q4



Roofline Scaling Trajectories

- Often, one plots performance as a function of thread concurrency
 - Carries no insight or analysis Ο
 - Provides no actionable information. \bigcirc







Roofline Scaling Trajectories

- Often, one plots performance as a function of thread concurrency
 - Carries no insight or analysis Ο
 - Provides no actionable information.
- Khaled Ibrahim developed a new way of using Roofline to analyze thread (or process) scalability
 - Create a 2D scatter plot of performance Ο as a function of AI and thread concurrency
 - Can identify loss in performance due to Ο increased cache pressure

Khaled Ibrahim, Samuel Williams, Leonid Oliker, "Roofline Scaling Trajectories: A Method for Parallel Application and Architectural Performance Analysis", HPCS Special Session on High Performance Computing Benchmarking and Optimization (HPBench), July 2018.

1000.0 Class A Class B Class C 0.00 GFlop/s 10.0 DRAM 1.0 0.1 0.05 0.50 0.01



roofline summary sp lbl





Roofline Scaling Trajectories

Observe...

- AI (data movement) varies with both Ο thread concurrency and problem size
- Large problems (green and red) move Ο much more data per thread, and eventually exhaust cache capacity
- Resultant fall in AI means they hit the Ο bandwidth ceiling quickly and degrade.
- Smaller problems see reduced AI, but Ο don't hit the bandwidth ceiling



roofline summary sp lbl





Broadly speaking, there are three approaches to improving performance:





Peak Flop/s No FMA

No vectorization



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- Maximize in-core performance (e.g. get compiler to vectorize)







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Peak Flop/s No FMA



- Broadly speaking, there are three approaches to improving performance:
- Maximize in-core performance (e.g. get compiler to vectorize)
- Maximize memory bandwidth (e.g. NUMA-aware, unit stride)
- Minimize data movement (e.g. cache blocking)









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Summary







- In this talk, we introduced several concepts...
 - Basic terminology (bandwidth, flop/s, arithmetic intensity) Ο
 - How to refine the Roofline to account for the memory hierarchy Ο
 - How to refine the Roofline to account for complex core architectures \bigcirc
 - How to map the 3Cs of Caches onto the Roofline model \bigcirc
 - General approaches to constructing a Roofline model for a machine and application Ο
 - How to use the Roofline model \bigcirc




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Questions?







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Backup



