Chapter 6

Parallel Processors from Client to Cloud

Part I

Introduction

- Goal: connecting multiple computers to get higher performance
  - Multiprocessors
  - Scalability, availability, power efficiency
- Task-level (process-level) parallelism
  - High throughput for independent jobs
- Parallel processing program
  - Single program run on multiple processors
- Multicore microprocessors
  - Chips with multiple processors (cores)

Hardware and Software

- Hardware
  - Serial: e.g., Pentium 4
  - Parallel: e.g., quad-core Xeon e5345
- Software
  - Sequential: e.g., matrix multiplication
  - Concurrent: e.g., operating system
- Sequential/concurrent software can run on serial/parallel hardware
  - Challenge: making effective use of parallel hardware

What We've Already Covered

- §2.11: Parallelism and Instructions
  - Synchronization
- §3.6: Parallelism and Computer Arithmetic
  - Subword Parallelism
- §4.11: Parallelism via Instructions
- §5.10: Parallelism and Memory Hierarchies
  - Cache Coherence

Parallel Programming

- Parallel software is the problem
- Need to get significant performance improvement
  - Otherwise, just use a faster uniprocessor, since it's easier!
- Difficulties
  - Partitioning
  - Coordination
  - Communications overhead

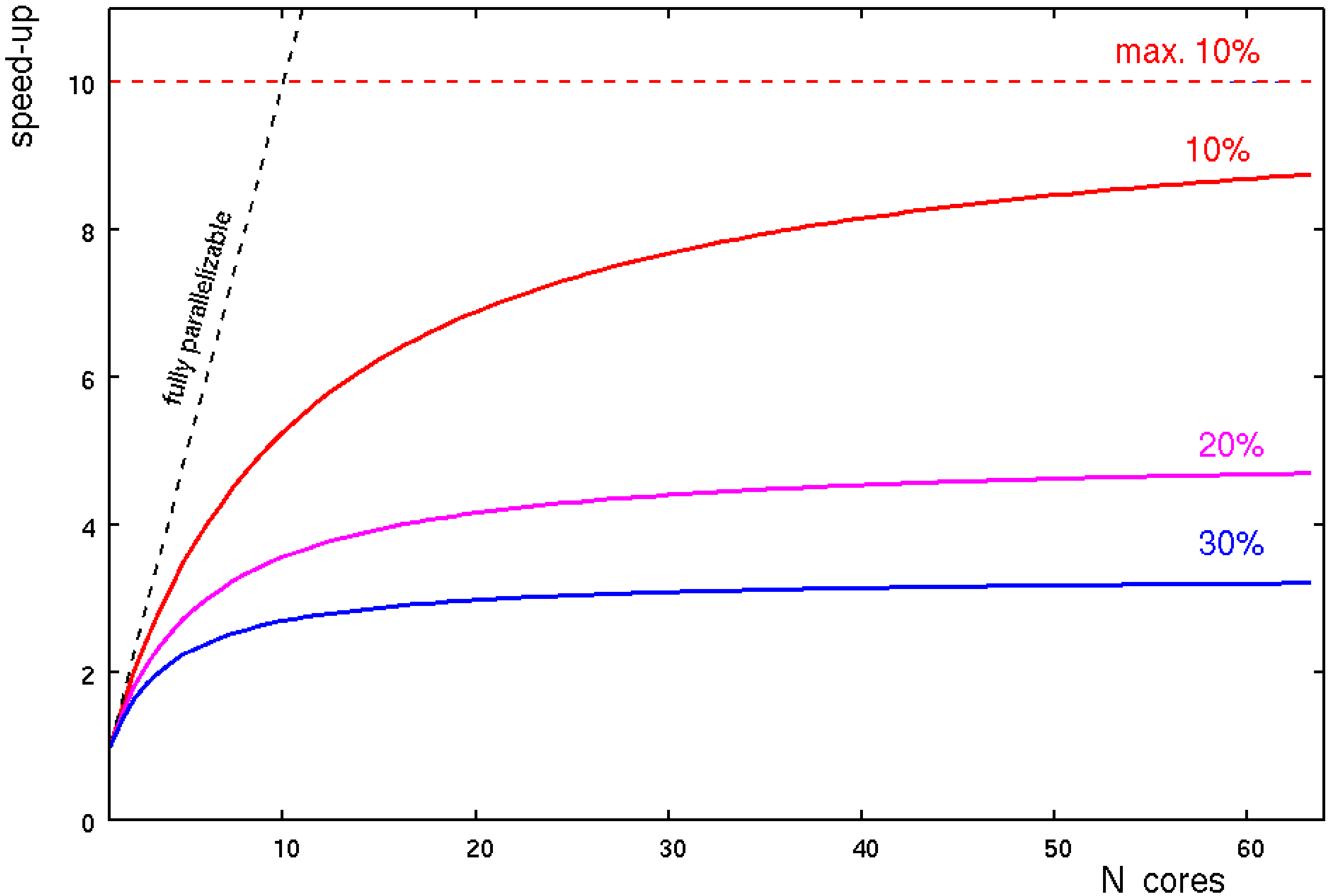
Amdahl's Law

- Sequential part can limit speedup
- Example: 100 processors, 90× speedup?
  - $T_{new} = T_{parallelizable}/100 + T_{sequential}$
  - $$\text{Speedup} = \frac{1}{(1 - F_{parallelizable}) + F_{parallelizable}/100} = 90$$
  - Solving: $F_{parallelizable} = 0.999$
- Need sequential part to be 0.1% of original time

Amdahl's Law (2)

If we have N cores

$$\text{Speedup} = \frac{1}{(1 - F_{\text{parallelizable}}) + F_{\text{parallelizable}}/N}$$



Scaling Example

- Workload: sum of 10 scalars, and 10 × 10 matrix sum
  - Speed up from 10 to 100 processors
- Single processor: Time = $(10 + 100) \times t_{add}$
- 10 processors
  - Time = $10 \times t_{add} + 100/10 \times t_{add} = 20 \times t_{add}$
  - Speedup = 110/20 = 5.5 (55% of potential)
- 100 processors
  - Time = $10 \times t_{add} + 100/100 \times t_{add} = 11 \times t_{add}$
  - Speedup = 110/11 = 10 (10% of potential)
- Assumes load can be balanced across processors

Scaling Example (cont)

- What if matrix size is 100 × 100?
- Single processor: Time = (10 + 10000) × t_{add}
- 10 processors
  - Time = 10 × t_{add} + 10000/10 × t_{add} = 1010 × t_{add}
  - Speedup = 10010/1010 = 9.9 (99% of potential)
- 100 processors
  - Time = 10 × t_{add} + 10000/100 × t_{add} = 110 × t_{add}
  - Speedup = 10010/110 = 91 (91% of potential)
- Assuming load balanced

Weak Scaling

Problem size proportional to number of processors

(fixed problem size for processor)

- 10 processors, 10 × 10 matrix
  - Time = $10 \times t_{add} + 100/10 \times t_{add} = 20 \times t_{add}$
- 100 processors, 32 × 32 matrix
  - Time = $10 \times t_{add} + 1024/100 \times t_{add} \approx 20 \times t_{add}$
- Constant performance in this example

Instruction and Data Streams

- An alternate classification

		Data Streams	
		Single	Multiple
Instruction Streams	Single	**SISD**: Intel Pentium 4	**SIMD**: SSE instructions of x86
	Multiple	**MISD**: No examples today	**MIMD**: Intel Xeon e5345

- SPMD: Single Program Multiple Data
  - A parallel program on a MIMD computer
  - Conditional code for different processors

Vector Processors

- Highly pipelined function units
- Stream data from/to vector registers to units
  - Data collected from memory into registers
  - Results stored from registers to memory
- Example: Vector extension to RISC-V
  - v0 to v31: 32 × 64-element registers, (64-bit elements)
  - Vector instructions
    - `fld.v`, `fsd.v`: load/store vector
    - `fadd.d.v`: add vectors of double
    - `fadd.d.vs`: add scalar to each element of vector of double
- Significantly reduces instruction-fetch bandwidth

Example: DAXPY (Y = a × X + Y)

- Conventional RISC-V code:

```
       fld     f0,a(x3)     // load scalar a
       addi    x5,x19,512   // end of array X
loop:  fld     f1,0(x19)    // load x[i]
       fmul.d  f1,f1,f0     // a * x[i]
       fld     f2,0(x20)    // load y[i]
       fadd.d  f2,f2,f1     // a * x[i] + y[i]
       fsd     f2,0(x20)    // store y[i]
       addi    x19,x19,8    // increment index to x
       addi    x20,x20,8    // increment index to y
       bltu    x19,x5,loop  // repeat if not done
```

Vector RISC-V code:

```
       fld        f0,a(x3)     // load scalar a
       fld.v      v0,0(x19)    // load vector x
       fmul.d.vs  v0,v0,f0     // vector-scalar multiply
       fld.v      v1,0(x20)    // load vector y
       fadd.d.v   v1,v1,v0     // vector-vector add
       fsd.v      v1,0(x20)    // store vector y
```

Vector vs. Scalar

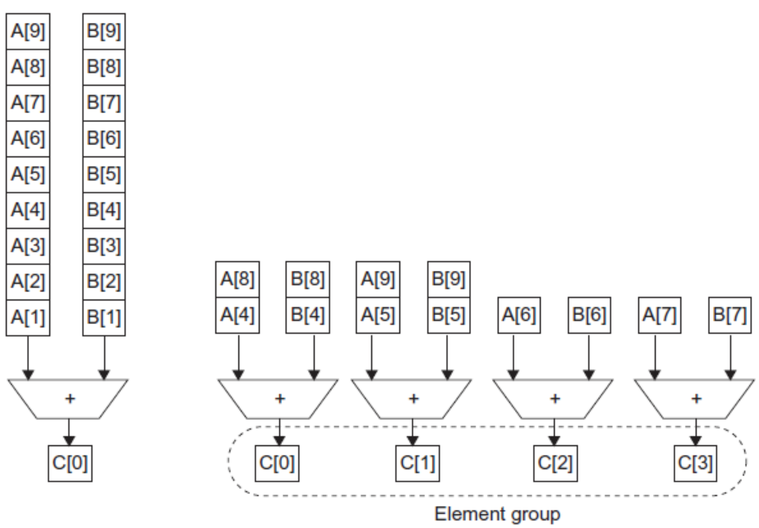
- Vector architectures and compilers
  - Simplify data-parallel programming
  - Explicit statement of absence of loop-carried dependences
    - Reduced checking in hardware
  - Regular access patterns benefit from interleaved and burst memory
  - Avoid control hazards by avoiding loops
- More general than ad-hoc media extensions (such as MMX, SSE)
  - Better match with compiler technology

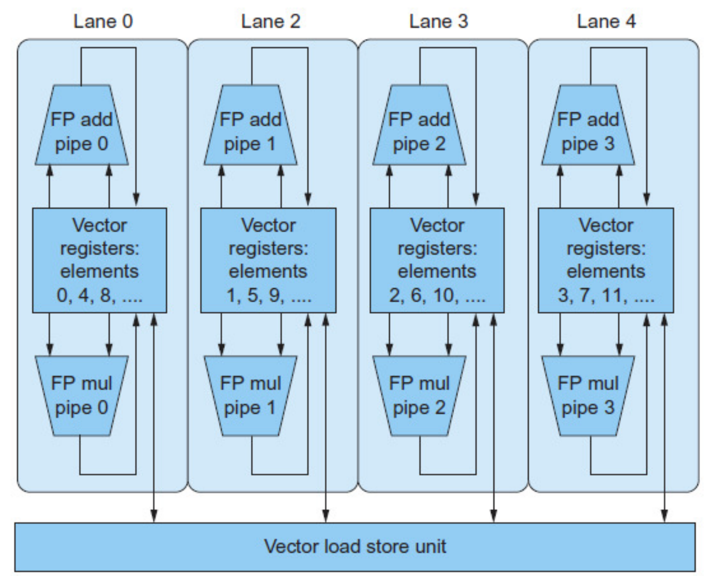
SIMD

- Operate elementwise on vectors of data
  - E.g., MMX and SSE instructions in x86
    - Multiple data elements in 128-bit wide registers
- All processors execute the same instruction at the same time
  - Each with different data address, etc.
- Simplifies synchronization
- Reduced instruction control hardware
- Works best for highly data-parallel applications

Vector vs. Multimedia Extensions

- Vector instructions have a variable vector width, multimedia extensions have a fixed width
- Vector instructions support strided access, multimedia extensions do not
- Vector units can be combination of pipelined and arrayed functional units:





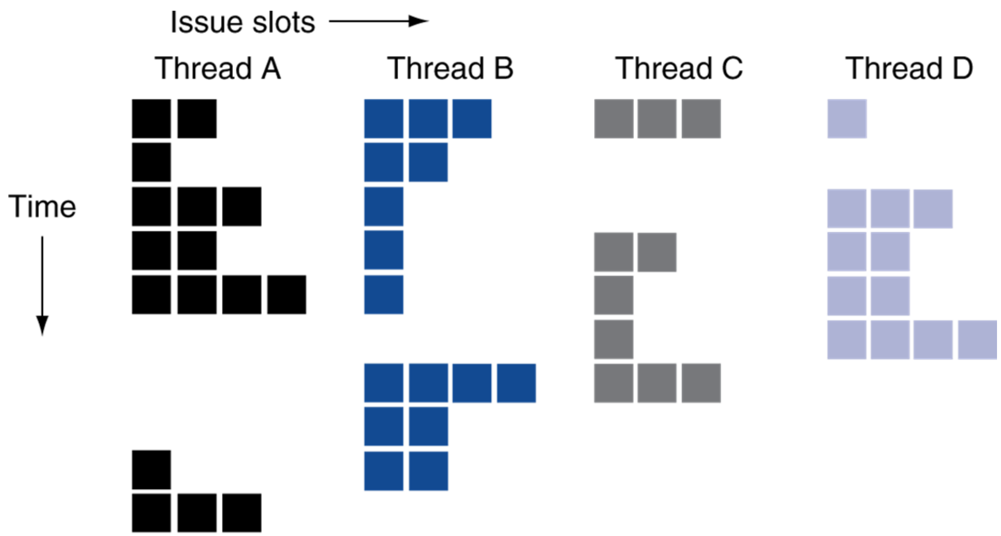
Multithreading

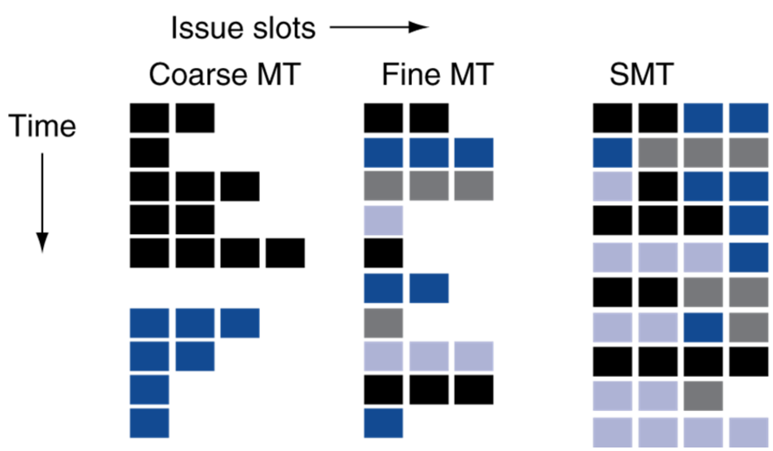
- Performing multiple threads of execution in parallel
  - Replicate registers, PC, etc.
  - Fast switching between threads
- Fine-grain multithreading
  - Switch threads after each cycle
  - Interleave instruction execution
  - If one thread stalls, others are executed
- Coarse-grain multithreading
  - Only switch on long stall (e.g., L2-cache miss)
  - Simplifies hardware, but doesn't hide short stalls (eg, data hazards)

Simultaneous Multithreading

- In multiple-issue dynamically scheduled processor
  - Schedule instructions from multiple threads
  - Instructions from independent threads execute when function units are available
  - Within threads, dependencies handled by scheduling and register renaming
- Example: Intel Pentium-4 HT
  - Two threads: duplicated registers, shared function units and caches

Multithreading Example



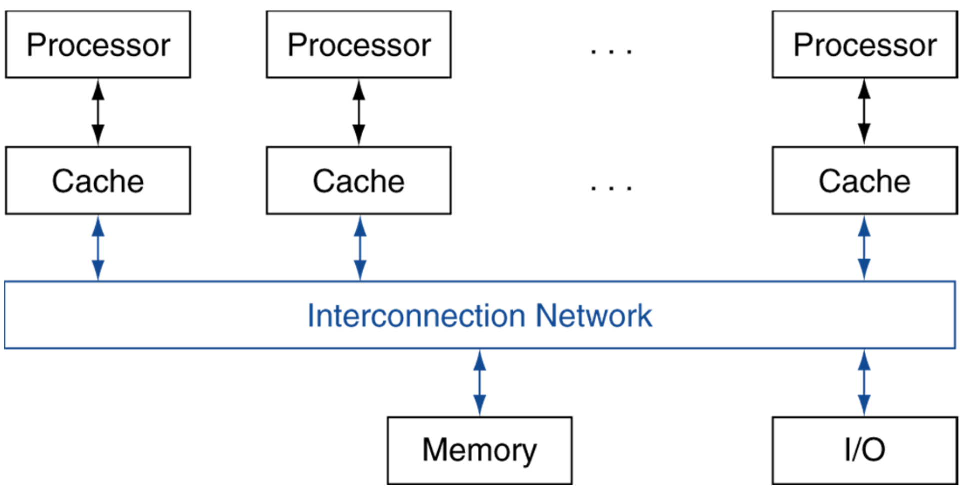


Future of Multithreading

- Will it survive? In what form?
- Power considerations $\Rightarrow$ simplified microarchitectures
  - Simpler forms of multithreading
- Tolerating cache-miss latency
  - Thread switch may be most effective
- Multiple simple cores might share resources more effectively

Shared Memory

- SMP: shared memory multiprocessor
  - Hardware provides single physical address space for all processors
  - Synchronize shared variables using locks
  - Memory access time
    - UMA (uniform) vs. NUMA (nonuniform)



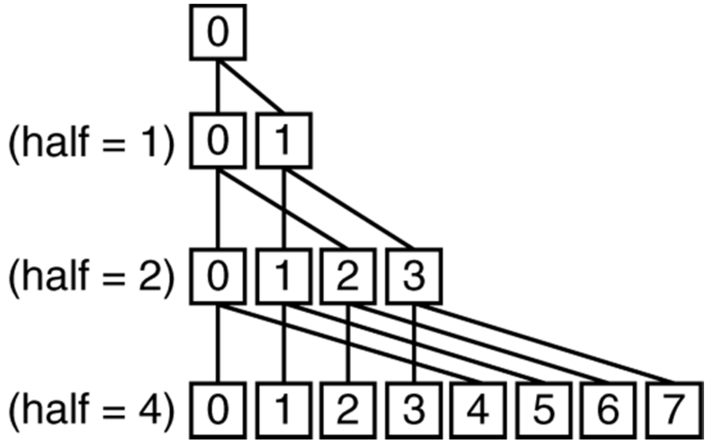
Example: Sum Reduction

- Sum 64,000 numbers on 64 processor UMA
  - Each processor has ID: $0 \leq Pn \leq 63$
  - Partition 1000 numbers per processor
  - Initial summation on each processor

```
sum[Pn] = 0;
  for (i = 1000*Pn;
          i < 1000*(Pn+1); i += 1)
     sum[Pn] += A[i];
```

- Now need to add these partial sums
  - Reduction: divide and conquer
  - Half the processors add pairs, then quarter, …
  - Need to synchronize between reduction steps

Example: Sum Reduction

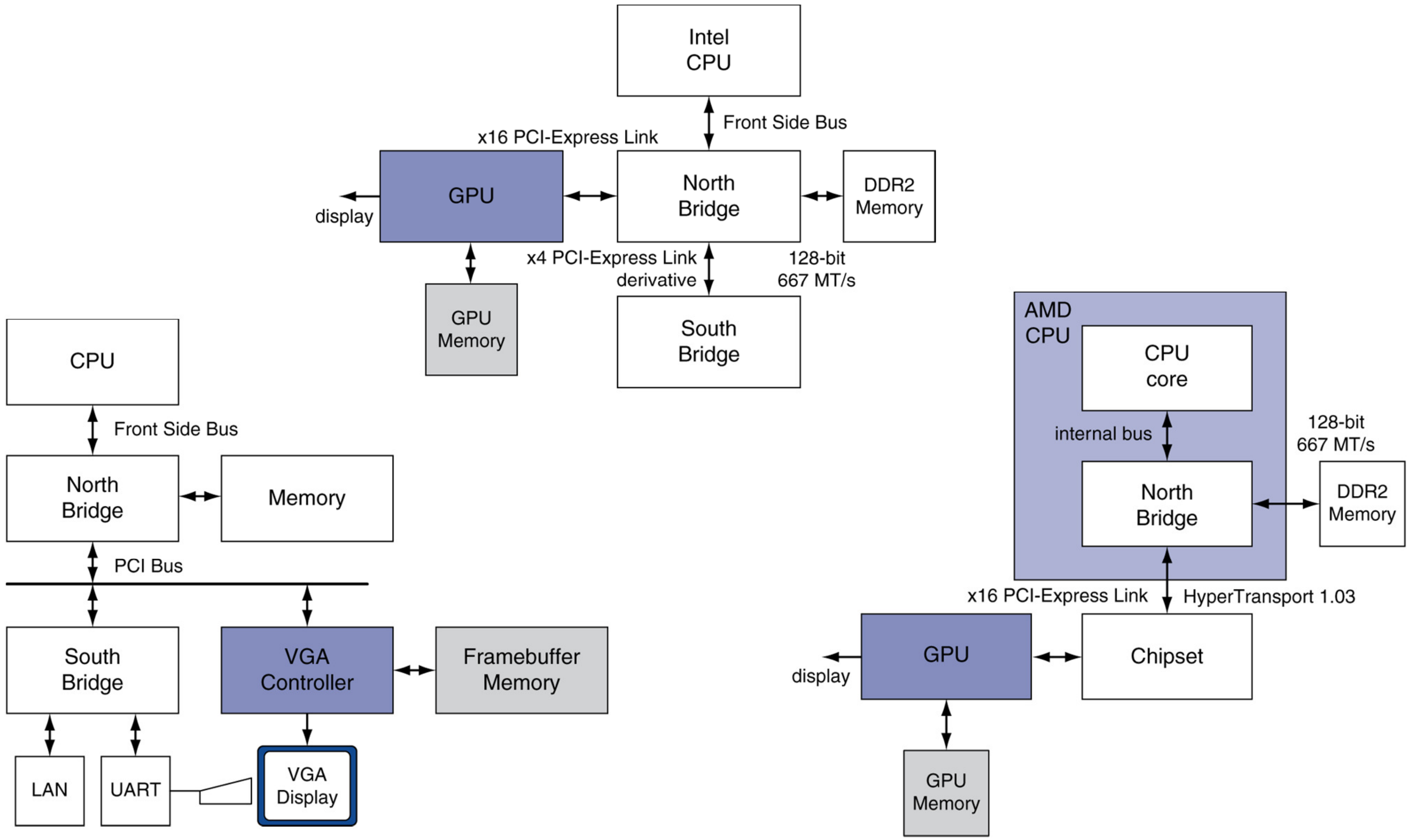



```
half = 64;
do
  synch();
  if (half%2 != 0 && Pn == 0)
    sum[0] += sum[half-1];
    /* Conditional sum needed when half is odd;
       Processor0 gets missing element */
  half = half/2; /* dividing line on who sums */
  if (Pn < half) sum[Pn] += sum[Pn+half];
while (half > 1);
```

History of GPUs

- Early video cards
  - Frame buffer memory with address generation for video output
- 3D graphics processing
  - Originally high-end computers (e.g., SGI)
  - Moore's Law ⇒ lower cost, higher density
  - 3D graphics cards for PCs and game consoles
- Graphics Processing Units
  - Processors oriented to 3D graphics tasks
  - Vertex/pixel processing, shading, texture mapping, rasterization

Graphics in the System

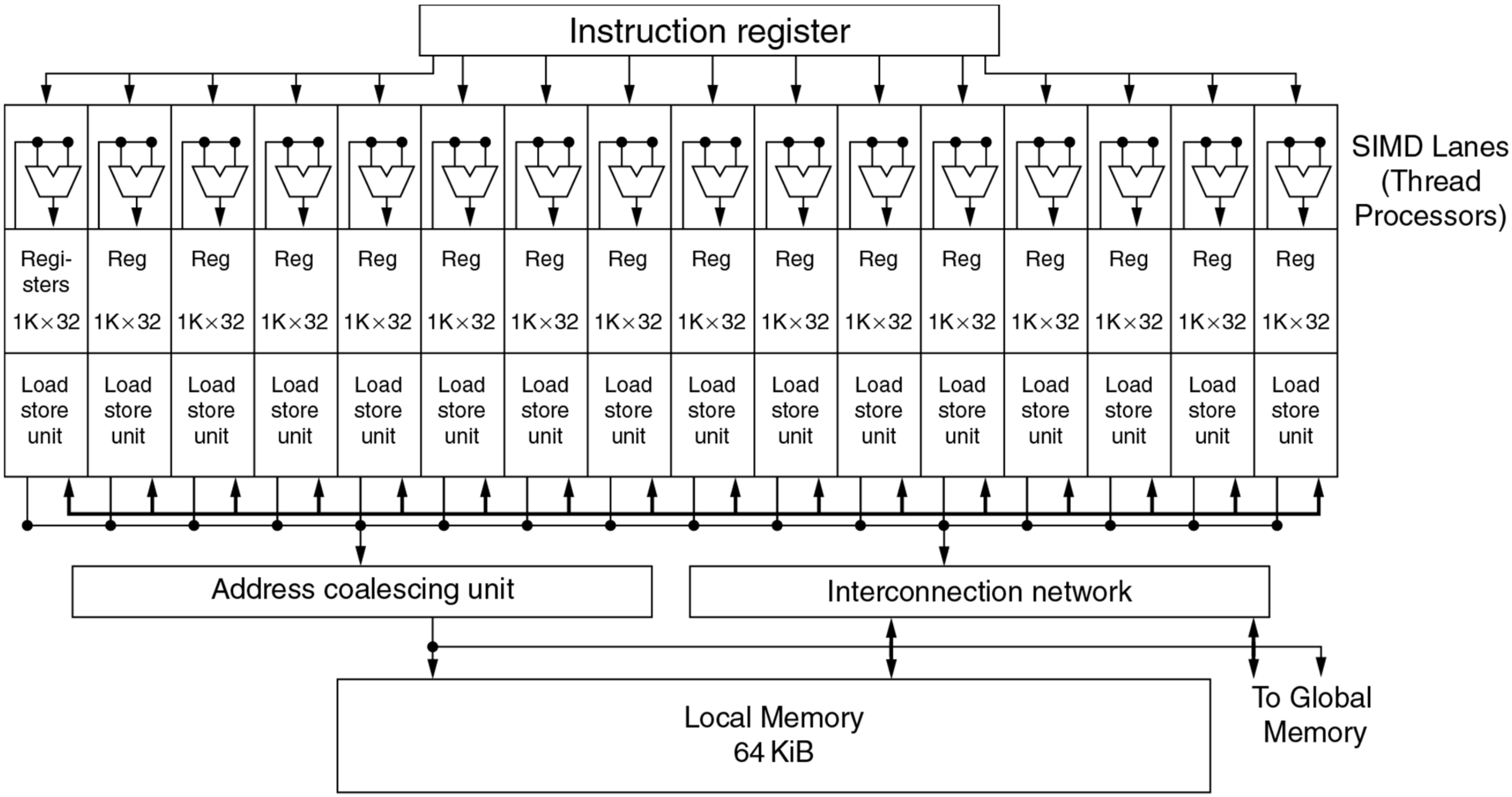


GPU Architectures

- Processing is highly data-parallel
  - GPUs are highly multithreaded
  - Use thread switching to hide memory latency
    - Less reliance on multi-level caches
  - Graphics memory is wide and high-bandwidth
- Trend toward general purpose GPUs
  - Heterogeneous CPU/GPU systems
  - CPU for sequential code, GPU for parallel code
- Programming languages/APIs
  - DirectX, OpenGL
  - C for Graphics (Cg), High Level Shader Language (HLSL)
  - Compute Unified Device Architecture (CUDA)

Example: NVIDIA Tesla

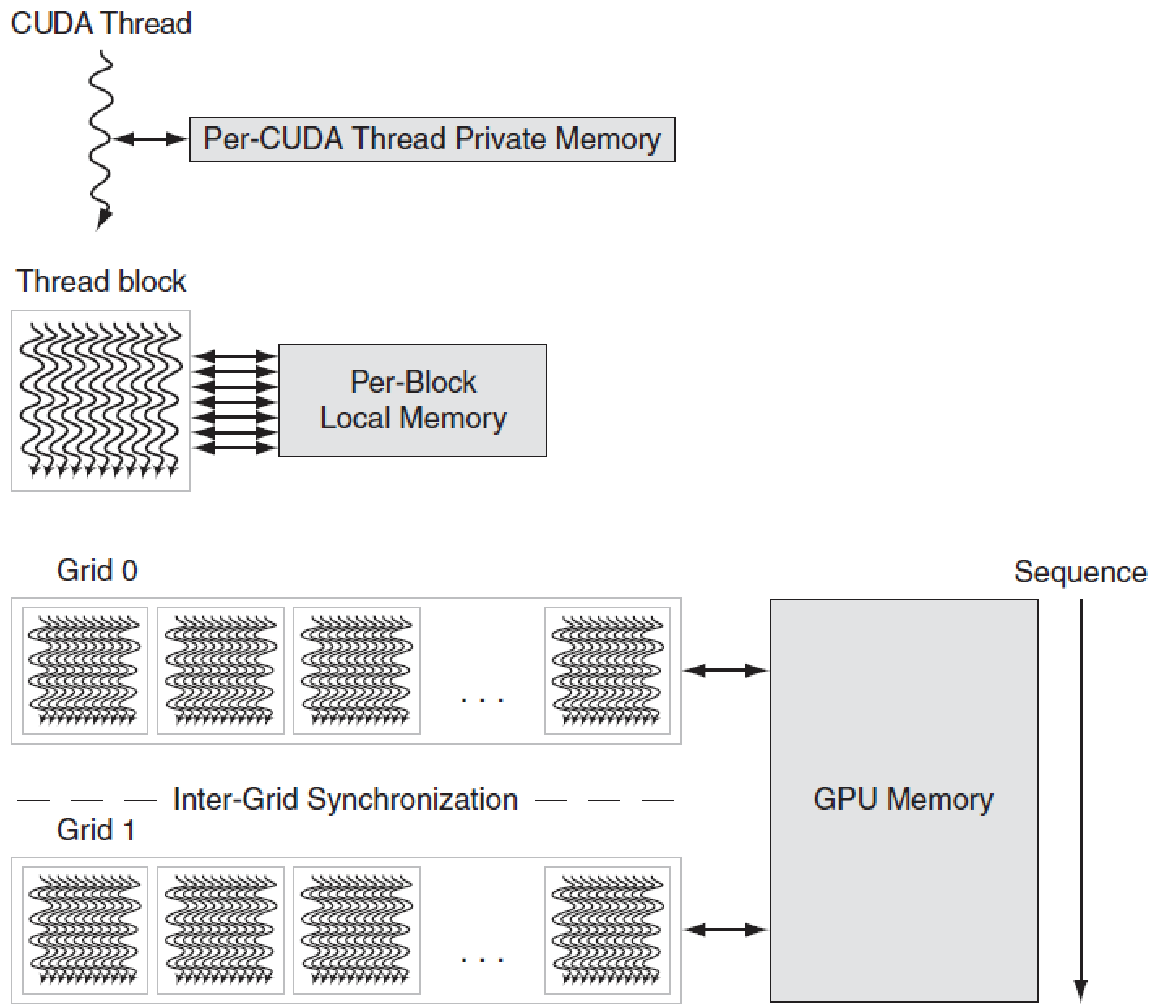
- Multiple SIMD processors, each as shown:



Example: NVIDIA Tesla

- SIMD Processor: 16 SIMD lanes
- SIMD instruction
  - Operates on 32 element wide threads
  - Dynamically scheduled on 16-wide processor over 2 cycles
- 32K x 32-bit registers spread across lanes
  - 64 registers per thread context

GPU Memory Structures



Classifying GPUs

- Don't fit nicely into SIMD/MIMD model
  - Conditional execution in a thread allows an illusion of MIMD
    - But with performance degredation
    - Need to write general purpose code with care

	Static: Discovered at Compile Time	Dynamic: Discovered at Runtime
Instruction-Level Parallelism	VLIW	Superscalar
Data-Level Parallelism	SIMD or Vector	**Tesla Multiprocessor**

Putting GPUs into Perspective

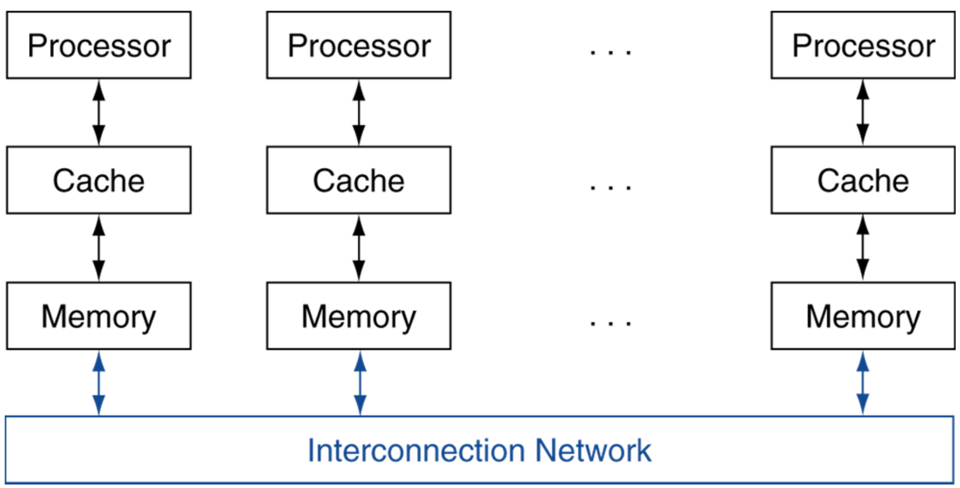
Feature	Multicore with SIMD	GPU
SIMD processors	8 to 24	15 to 80
SIMD lanes/processor	2 to 4	8 to 16
Multithreading hardware support for SIMD threads	2 to 4	16 to 32
Typical ratio of single precision to double-precision performance	2:1	2:1
Largest cache size	48 MB	6 MB
Size of memory address	64-bit	64-bit
Size of main memory	64 GB to 1024 GB	4 GB to 16 GB
Memory protection at level of page	Yes	Yes
Demand paging	Yes	No
Cache coherent	Yes	No

Guide to GPU Terms

Type	More descriptive name	Closest old term outside of GPUs	Official CUDA/ NVIDIA GPU term	Book definition
Program abstractions	Vectorizable Loop	Vectorizable Loop	Grid	A vectorizable loop, executed on the GPU, made up of one or more Thread Blocks (bodies of vectorized loop) that can execute in parallel.
	Body of Vectorized Loop	Body of a (Strip-Mined) Vectorized Loop	Thread Block	A vectorized loop executed on a multithreaded SIMD Processor, made up of one or more threads of SIMD instructions. They can communicate via Local Memory.
	Sequence of SIMD Lane Operations	One iteration of a Scalar Loop	CUDA Thread	A vertical cut of a thread of SIMD instructions corresponding to one element executed by one SIMD Lane. Result is stored depending on mask and predicate register.
Machine object	A Thread of SIMD Instructions	Thread of Vector Instructions	Warp	A traditional thread, but it contains just SIMD instructions that are executed on a multithreaded SIMD Processor. Results stored depending on a per-element mask.
	SIMD Instruction	Vector Instruction	PTX Instruction	A single SIMD instruction executed across SIMD Lanes.
Processing hardware	Multithreaded SIMD Processor	(Multithreaded) Vector Processor	Streaming Multiprocessor	A multithreaded SIMD Processor executes threads of SIMD instructions, independent of other SIMD Processors.
	Thread Block Scheduler	Scalar Processor	Giga Thread Engine	Assigns multiple Thread Blocks (bodies of vectorized loop) to multithreaded SIMD Processors.
	SIMD Thread Scheduler	Thread scheduler in a Multithreaded CPU	Warp Scheduler	Hardware unit that schedules and issues threads of SIMD instructions when they are ready to execute; includes a scoreboard to track SIMD Thread execution.
	SIMD Lane	Vector lane	Thread Processor	A SIMD Lane executes the operations in a thread of SIMD instructions on a single element. Results stored depending on mask.
Memory hardware	GPU Memory	Main Memory	Global Memory	DRAM memory accessible by all multithreaded SIMD Processors in a GPU.
	Local Memory	Local Memory	Shared Memory	Fast local SRAM for one multithreaded SIMD Processor, unavailable to other SIMD Processors.
	SIMD Lane Registers	Vector Lane Registers	Thread Processor Registers	Registers in a single SIMD Lane allocated across a full thread block (body of vectorized loop).

Message Passing

- Each processor has private physical address space
- Hardware sends/receives messages between processors



Loosely Coupled Clusters

- Network of independent computers
  - Each has private memory and OS
  - Connected using I/O system
    - E.g., Ethernet/switch, Internet
- Suitable for applications with independent tasks
  - Web servers, databases, simulations, …
- High availability, scalable, affordable
- Problems
  - Administration cost (prefer virtual machines)
  - Low interconnect bandwidth
    - c.f. processor/memory bandwidth on an SMP

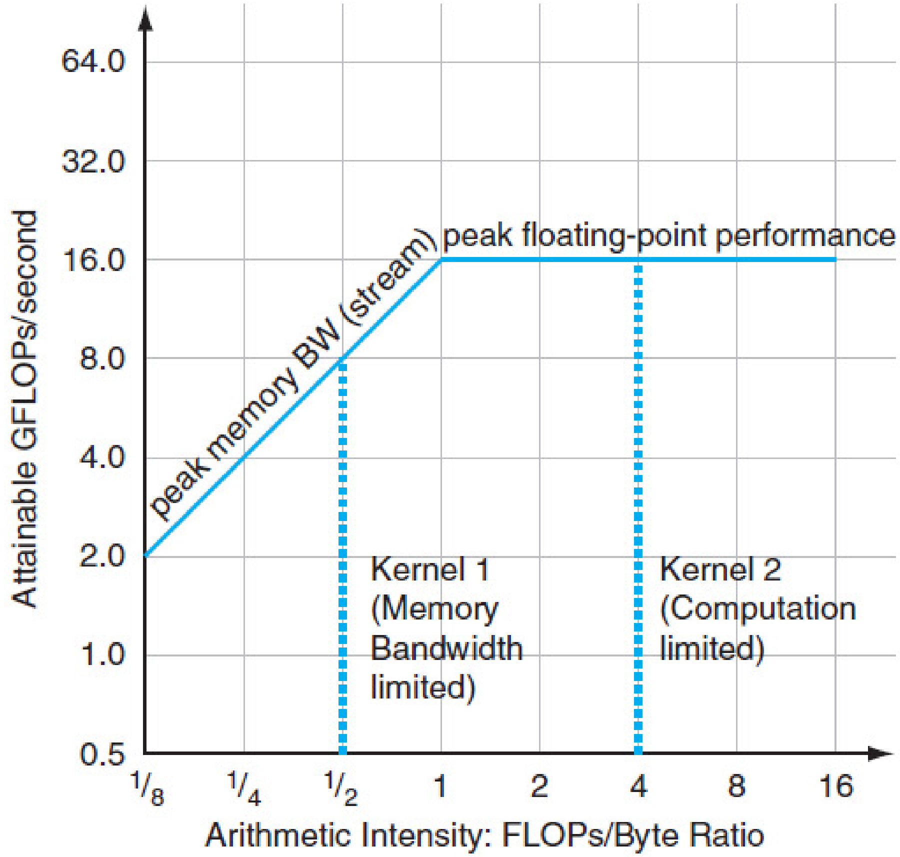
Grid Computing

- Separate computers interconnected by long-haul networks
  - E.g., Internet connections
  - Work units farmed out, results sent back
- Can make use of idle time on PCs
  - E.g., SETI@home, World Community Grid

Modeling Performance

- Assume performance metric of interest is achievable GFLOPs/sec
  - Measured using computational kernels from Berkeley Design Patterns
- Arithmetic intensity of a kernel
  - Ratio of FLOPs per byte of memory accessed
    (Total FP-ops) / (Total bytes transf. to Main Mem.)
- For a given computer, determine
  - Peak GFLOPS (from data sheet)
  - Peak memory bytes/sec (using Stream benchmark)

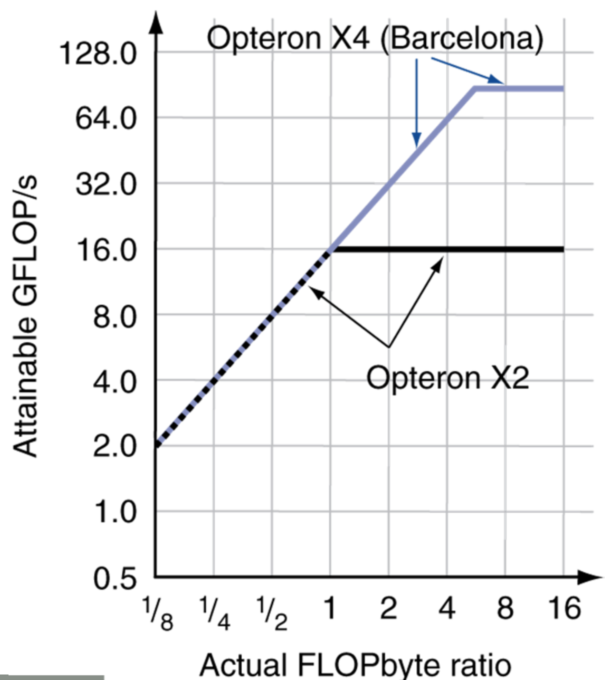
Roofline Diagram



Attainable GPLOPs/sec
= Max (Peak Memory BW × Arithmetic Intensity, Peak FP Performance)

Comparing Systems

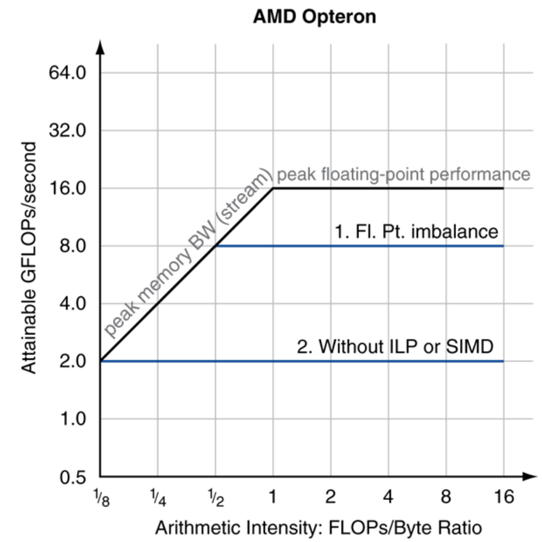
- Example: Opteron X2 vs. Opteron X4
  - 2-core vs. 4-core, 2 FP performance/core, 2.2GHz vs. 2.3GHz
  - Same memory system

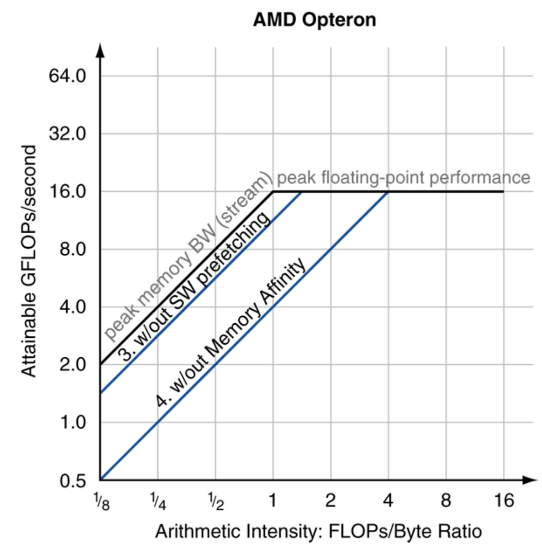


- To get higher performance on X4 than X2
  - Need high arithmetic intensity
  - Or working set must fit in X4's 2MB L-3 cache

Optimizing Performance

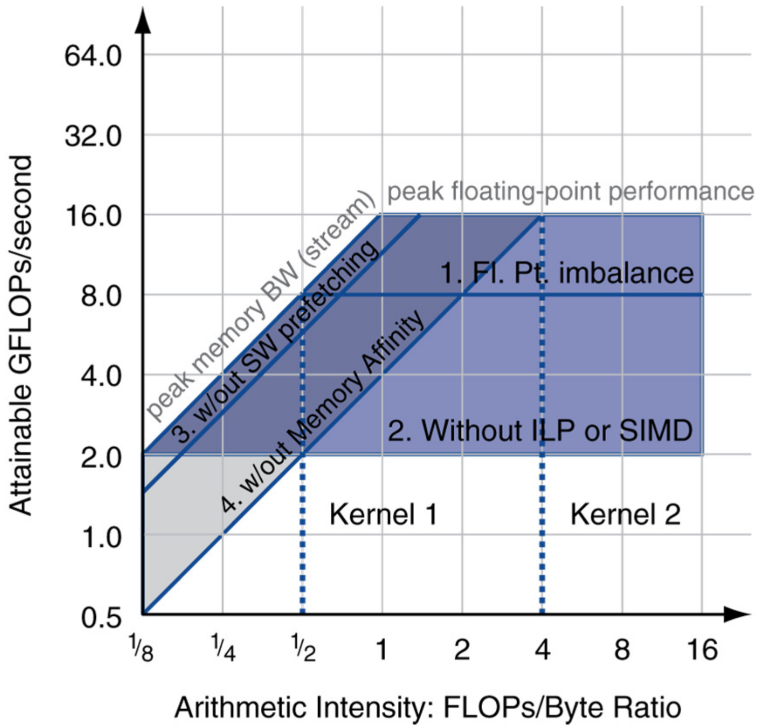
- Optimize FP performance
  - Balance adds & multiplies
  - Improve superscalar ILP and use of SIMD instructions
- Optimize memory usage
  - Software prefetch
    - Avoid load stalls
  - Memory affinity
    - Avoid non-local data accesses





Optimizing Performance

- Choice of optimization depends on arithmetic intensity of code



- Arithmetic intensity is not always fixed
  - May scale with problem size
  - Caching reduces memory accesses
    - Increases arithmetic intensity