



Chapter 7

Multicores, Multiprocessors, and Clusters

Introduction

- Goal: connecting multiple computers to get higher performance
 - Multiprocessors
 - Scalability, availability, power efficiency
- Job-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
 - Associativity
- §4.10: Parallelism and Advanced Instruction-Level Parallelism
- §5.8: Parallelism and Memory Hierarchies
 - Cache Coherence
- §6.9: Parallelism and I/O:
 - Redundant Arrays of Inexpensive Disks



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



Scaling Example

- Workload: sum of 10 scalars, and 10×10 matrix sum
 - Speed up from 10 to 100 processors
- Single processor: Time = $(10 + 100) \times t_{\text{add}}$
- 10 processors
 - Time = $10 \times t_{\text{add}} + 100/10 \times t_{\text{add}} = 20 \times t_{\text{add}}$
 - Speedup = $110/20 = 5.5$ (55% of potential)
- 100 processors
 - Time = $10 \times t_{\text{add}} + 100/100 \times t_{\text{add}} = 11 \times t_{\text{add}}$
 - 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 = $(10 + 10000) \times t_{\text{add}}$
- 10 processors
 - Time = $10 \times t_{\text{add}} + 10000/10 \times t_{\text{add}} = 1010 \times t_{\text{add}}$
 - Speedup = $10010/1010 = 9.9$ (99% of potential)
- 100 processors
 - Time = $10 \times t_{\text{add}} + 10000/100 \times t_{\text{add}} = 110 \times t_{\text{add}}$
 - Speedup = $10010/110 = 91$ (91% of potential)
- Assuming load balanced

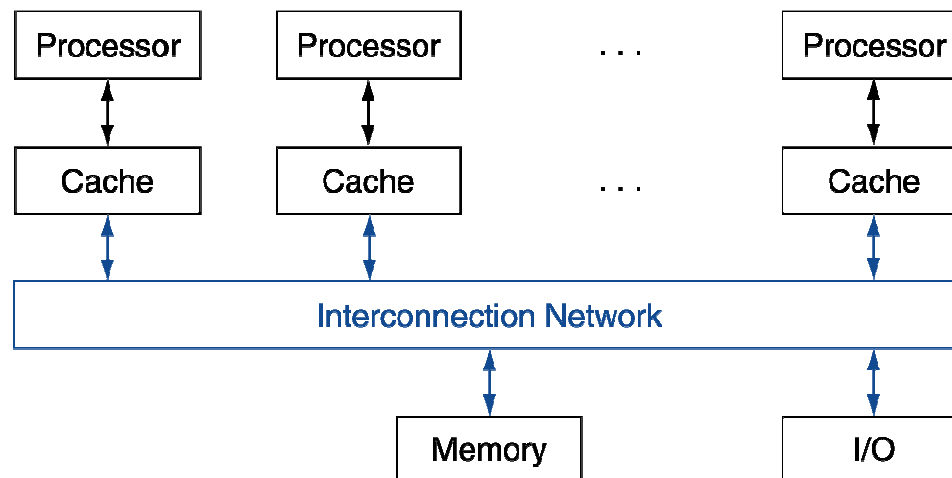
Strong vs Weak Scaling

- Strong scaling: problem size fixed
 - As in example
- Weak scaling: problem size proportional to number of processors
 - 10 processors, 10×10 matrix
 - Time = $20 \times t_{\text{add}}$
 - 100 processors, 32×32 matrix
 - Time = $10 \times t_{\text{add}} + 1000/100 \times t_{\text{add}} = 20 \times t_{\text{add}}$
 - Constant performance in this example



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 100,000 numbers on 100 processor UMA
 - Each processor has ID: $0 \leq P_n \leq 99$
 - Partition 1000 numbers per processor
 - Initial summation on each processor

```
sum[Pn] = 0;
for (i = 1000*Pn;
     i < 1000*(Pn+1); i = i + 1)
    sum[Pn] = 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 = 100;  
repeat
```

```
  synch();
```

```
  if (half%2 != 0 && Pn == 0)
```

```
    sum[0] = sum[0] + sum[half-1];
```

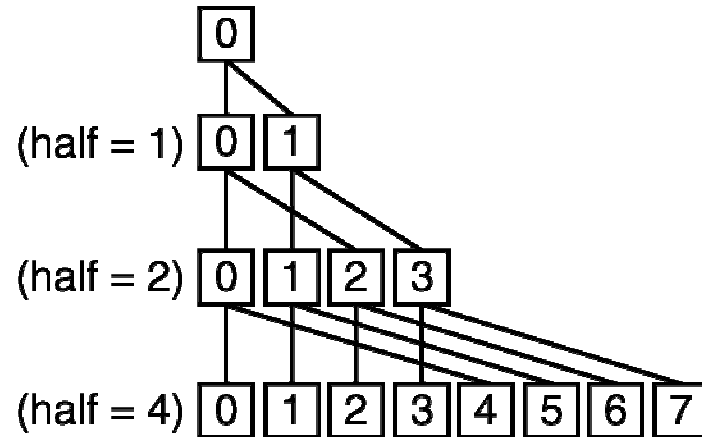
```
    /* Conditional sum needed when half is odd;
```

```
       Processor0 gets missing element */
```

```
  half = half/2; /* dividing line on who sums */
```

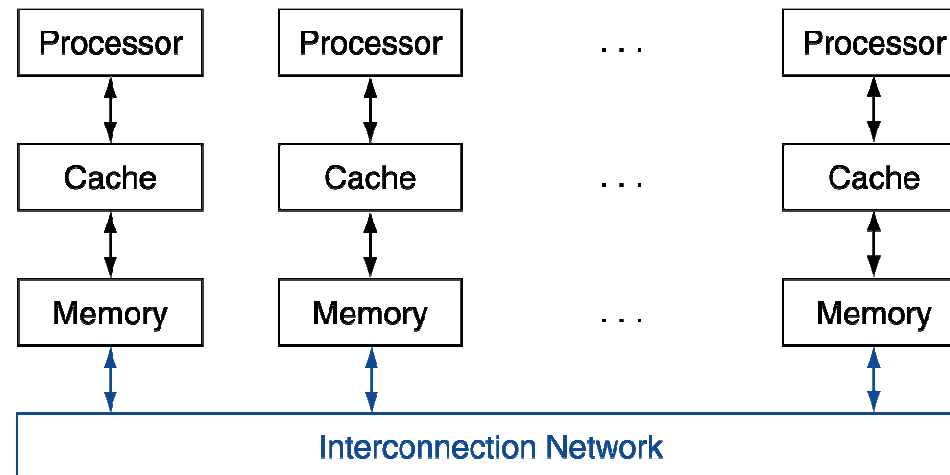
```
  if (Pn < half) sum[Pn] = sum[Pn] + sum[Pn+half];
```

```
until (half == 1);
```



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



Sum Reduction (Again)

- Sum 100,000 on 100 processors
- First distribute 100 numbers to each
 - They do partial sums

```
sum = 0;
for (i = 0; i < 1000; i = i + 1)
    sum = sum + AN[i];
```
- Reduction
 - Half the processors send, other half receive and add
 - The quarter send, quarter receive and add, ...



Sum Reduction (Again)

- Given send() and receive() operations

```
limit = 100; half = 100; /* 100 processors */
repeat
    half = (half+1)/2; /* send vs. receive
                        dividing line */
    if (Pn >= half && Pn < limit)
        send(Pn - half, sum);
    if (Pn < (limit/2))
        sum = sum + receive();
    limit = half; /* upper limit of senders */
until (half == 1); /* exit with final sum */
```

- Send/receive also provide synchronization
- Assumes send/receive take similar time to addition



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



Multithreading

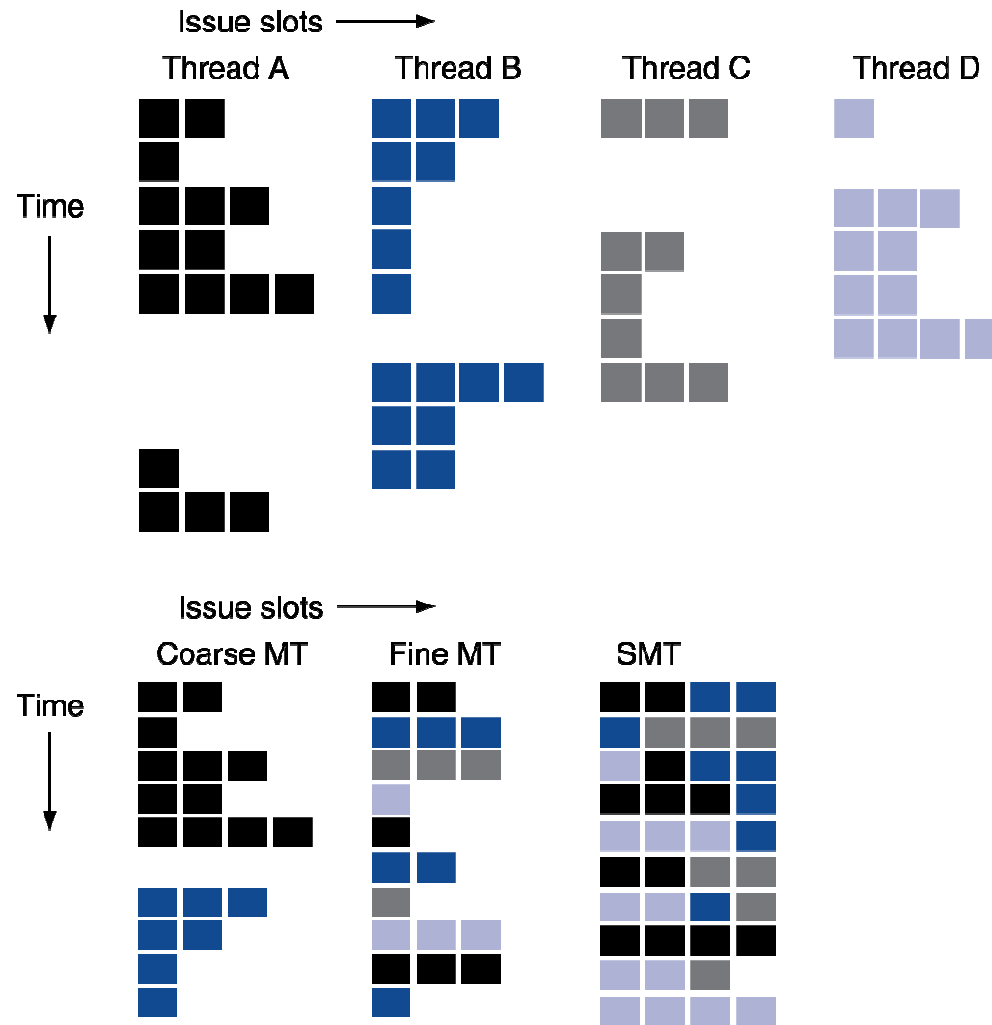
- Performing multiple threads of execution in parallel
 - Replicate registers, PC, etc.
 - Fast switching between threads
- Fine-grain multithreading
 - Switch threads after each cycle
 - Interleave instruction execution
 - If one thread stalls, others are executed
- Coarse-grain multithreading
 - Only 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



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



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 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 MIPS
 - 32×64 -element registers (64-bit elements)
 - Vector instructions
 - `lv, sv`: load/store vector
 - `addv.d`: add vectors of double
 - `addvs.d`: add scalar to each element of vector of double
- Significantly reduces instruction-fetch bandwidth



Example: DAXPY ($Y = a \times X + Y$)

- Conventional MIPS code

```
l.d    $f0, a($sp)           ;load scalar a
addiu  r4, $s0, #512         ;upper bound of what to load
loop:  l.d    $f2, 0($s0)      ;load x(i)
      mul.d  $f2, $f2, $f0     ;a x x(i)
      l.d    $f4, 0($s1)      ;load y(i)
      add.d  $f4, $f4, $f2     ;a x x(i) + y(i)
      s.d    $f4, 0($s1)      ;store into y(i)
      addiu  $s0, $s0, #8      ;increment index to x
      addiu  $s1, $s1, #8      ;increment index to y
      subu   $t0, r4, $s0      ;compute bound
      bne   $t0, $zero, loop  ;check if done
```

- Vector MIPS code

```
l.d    $f0, a($sp)           ;load scalar a
lv     $v1, 0($s0)            ;load vector x
mulvs.d $v2, $v1, $f0         ;vector-scalar multiply
lv     $v3, 0($s1)            ;load vector y
addv.d $v4, $v2, $v3         ;add y to product
sv     $v4, 0($s1)            ;store the result
```



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

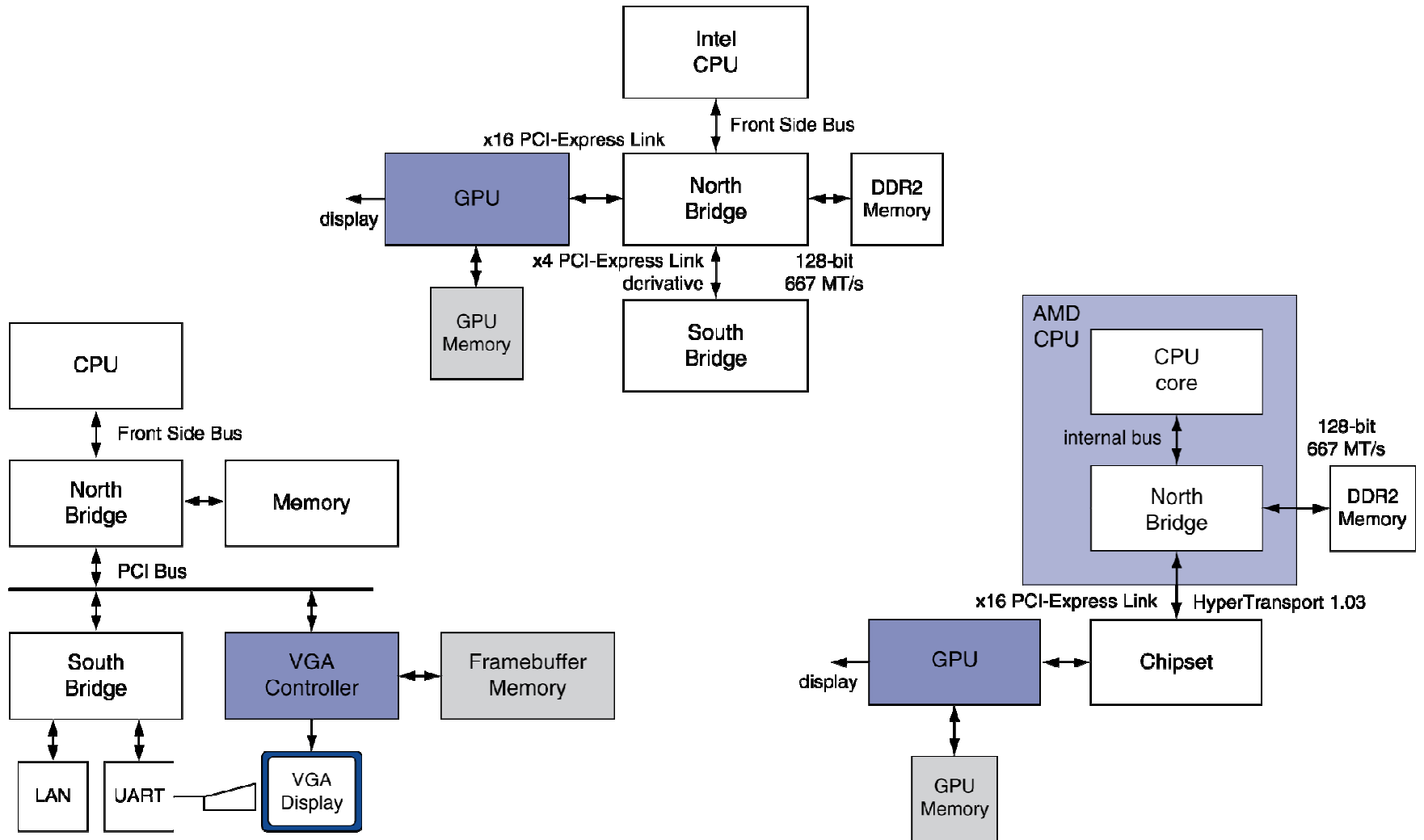


History of GPUs

- 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 \Rightarrow 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

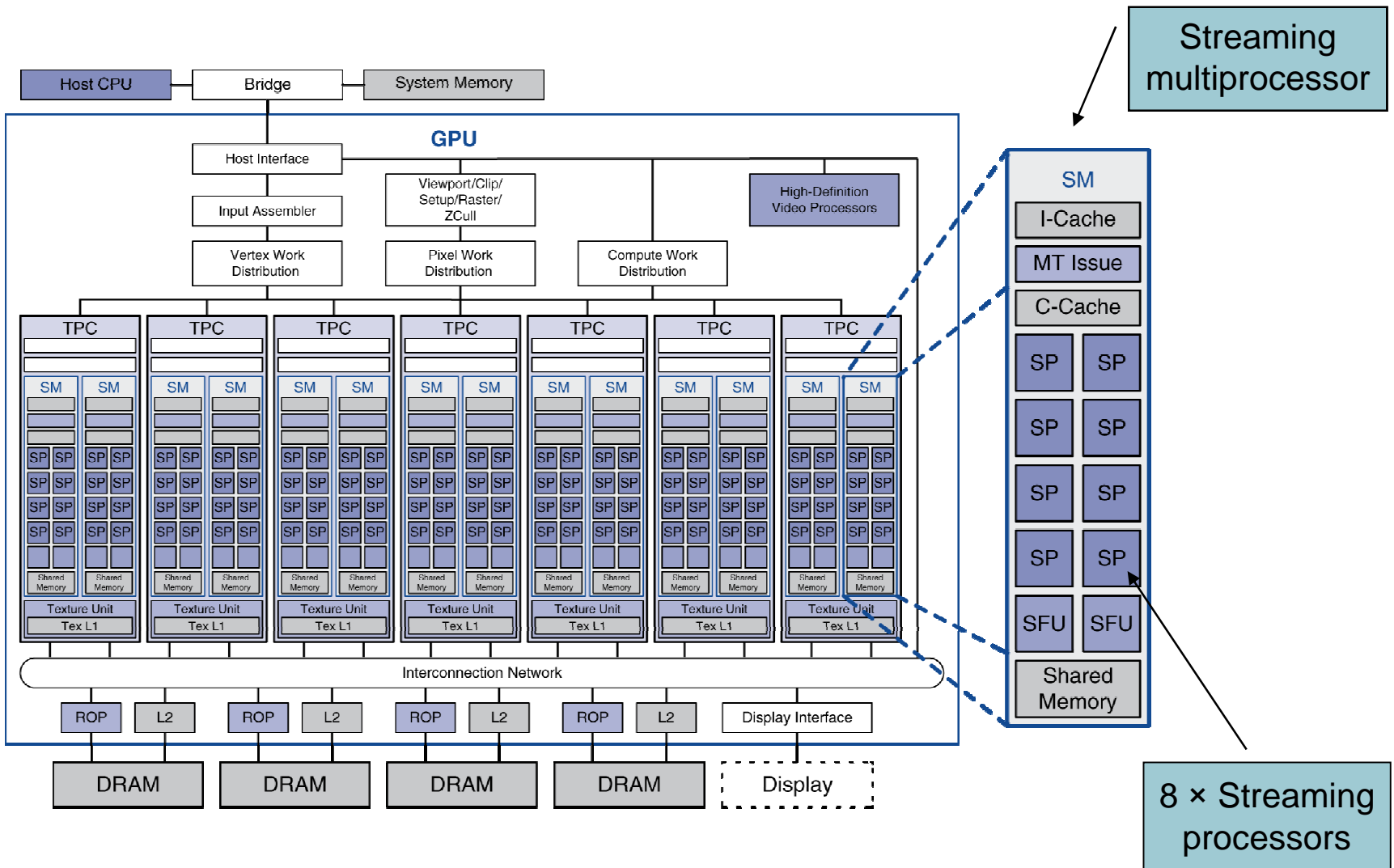


GPU Architectures

- 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)

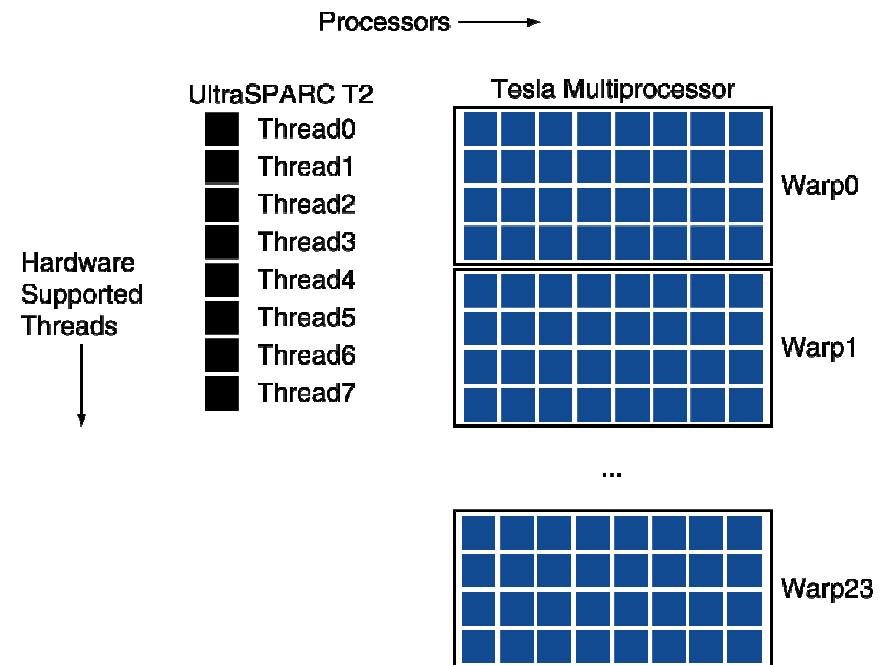


Example: NVIDIA Tesla



Example: NVIDIA Tesla

- Streaming Processors
 - Single-precision FP and integer units
 - Each SP is fine-grained multithreaded
- Warp: group of 32 threads
 - Executed in parallel, SIMD style
 - 8 SPs × 4 clock cycles
 - Hardware contexts for 24 warps
 - Registers, PCs, ...



Classifying GPUs

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

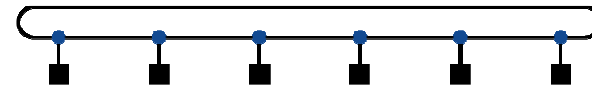
	Static: Discovered at Compile Time	Dynamic: Discovered at Runtime
Instruction-Level Parallelism	VLIW	Superscalar
Data-Level Parallelism	SIMD or Vector	Tesla Multiprocessor

Interconnection Networks

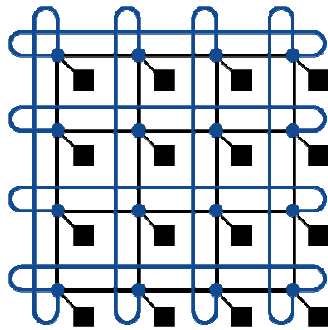
- Network topologies
 - Arrangements of processors, switches, and links



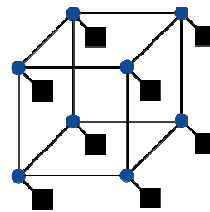
Bus



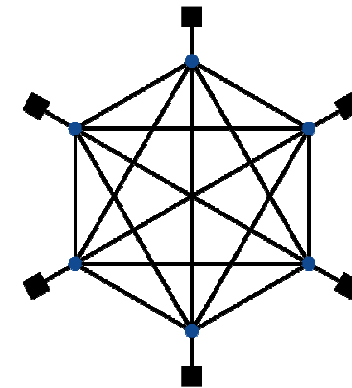
Ring



2D Mesh

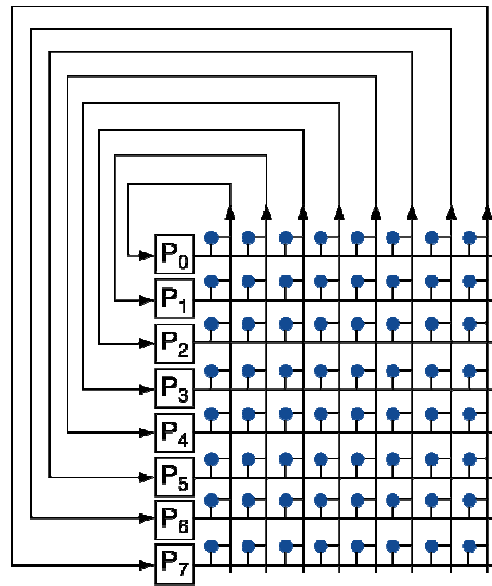


N-cube (N = 3)

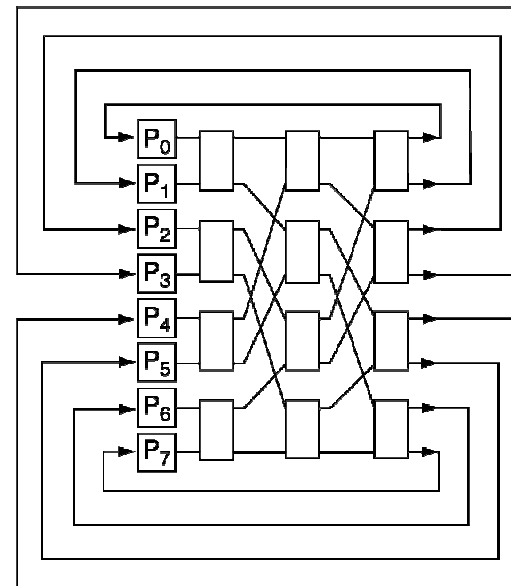


Fully connected

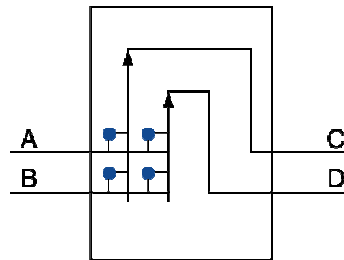
Multistage Networks



a. Crossbar



b. Omega network



c. Omega network switch box

Network Characteristics

- Performance
 - Latency per message (unloaded network)
 - Throughput
 - Link bandwidth
 - Total network bandwidth
 - Bisection bandwidth
 - Congestion delays (depending on traffic)
- Cost
- Power
- Routability in silicon



Parallel Benchmarks

- Linpack: matrix linear algebra
- SPECrate: parallel run of SPEC CPU programs
 - Job-level parallelism
- SPLASH: Stanford Parallel Applications for Shared Memory
 - Mix of kernels and applications, strong scaling
- NAS (NASA Advanced Supercomputing) suite
 - computational fluid dynamics kernels
- PARSEC (Princeton Application Repository for Shared Memory Computers) suite
 - Multithreaded applications using Pthreads and OpenMP



Code or Applications?

- Traditional benchmarks
 - Fixed code and data sets
- Parallel programming is evolving
 - Should algorithms, programming languages, and tools be part of the system?
 - Compare systems, provided they implement a given application
 - E.g., Linpack, Berkeley Design Patterns
- Would foster innovation in approaches to parallelism

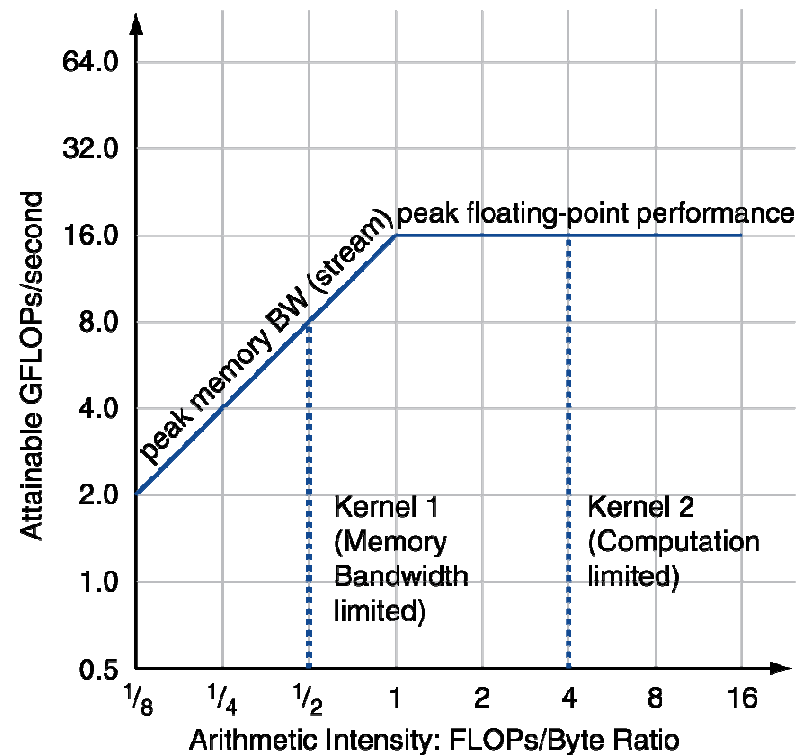


Modeling Performance

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



Roofline Diagram

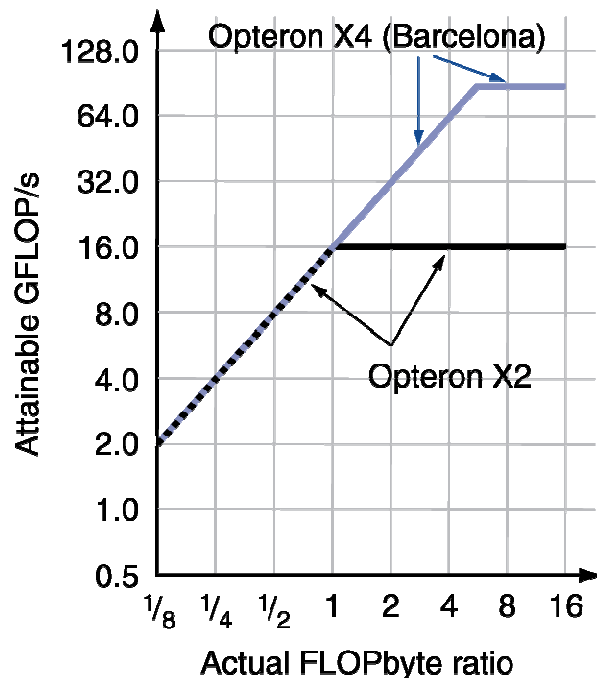


Attainable GPLOPs/sec
= Max (Peak Memory BW × Arithmetic Intensity, Peak FP Performance)



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

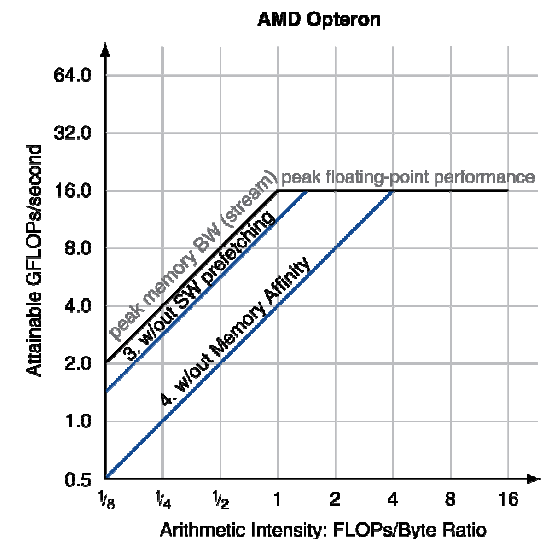
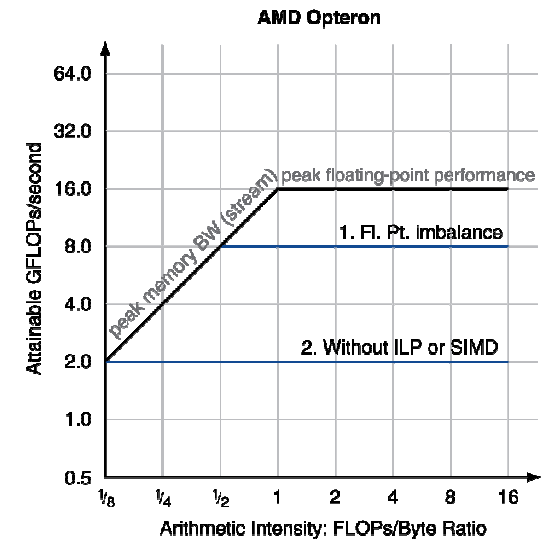


- To get higher performance on X4 than X2
 - Need high arithmetic intensity
 - Or working set must fit in X4's 2MB L-3 cache



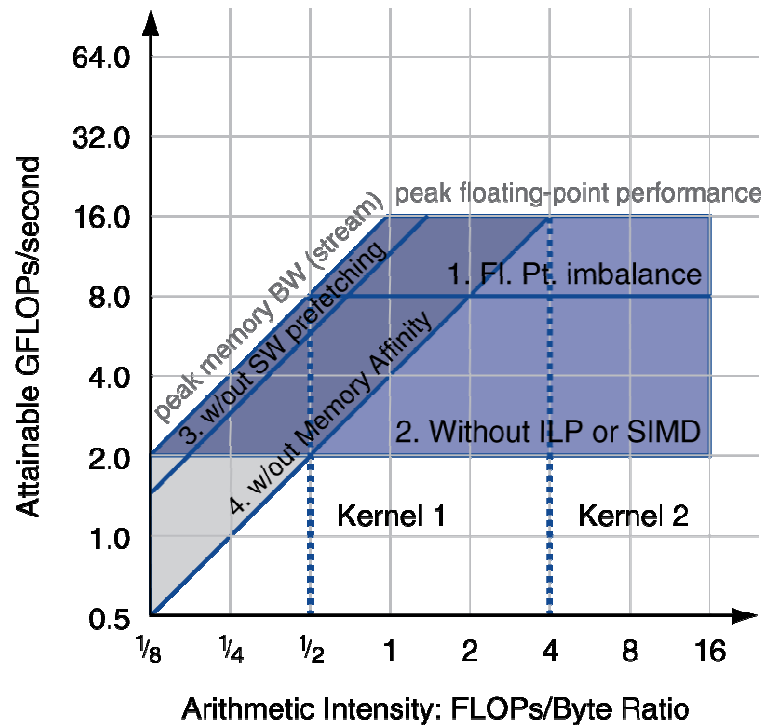
Optimizing Performance

- 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

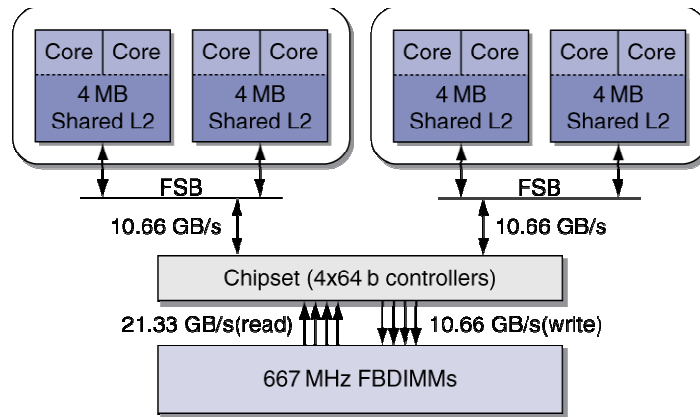
- Choice of optimization depends on arithmetic intensity of code



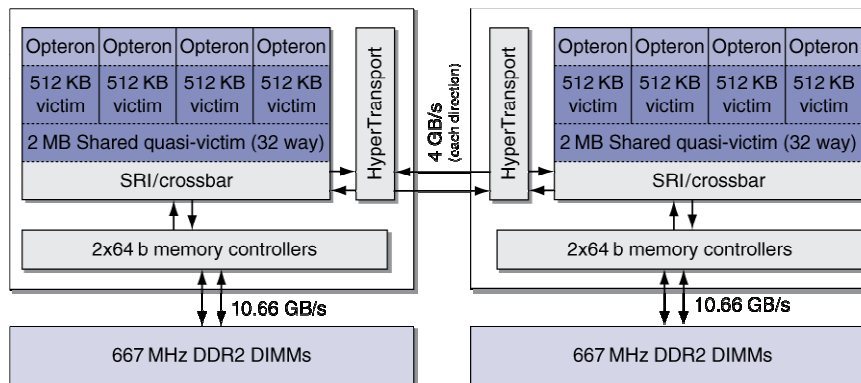
- Arithmetic intensity is not always fixed
 - May scale with problem size
 - Caching reduces memory accesses
 - Increases arithmetic intensity



Four Example Systems



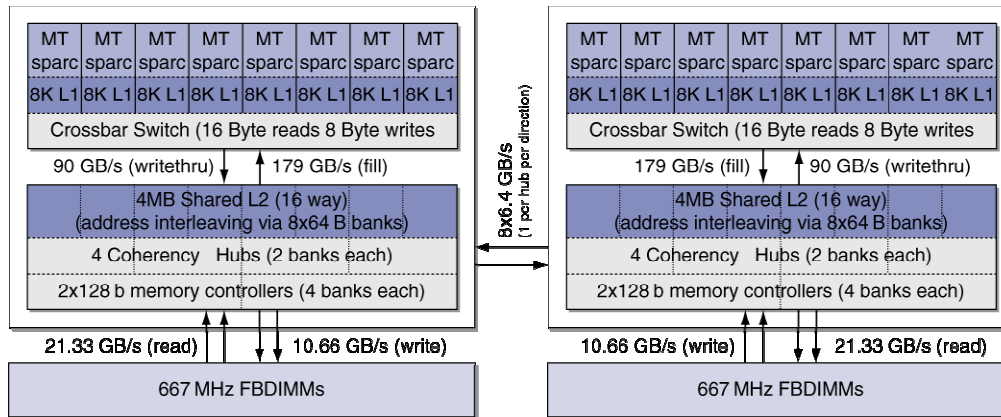
2 × quad-core
Intel Xeon e5345
(Clovertown)



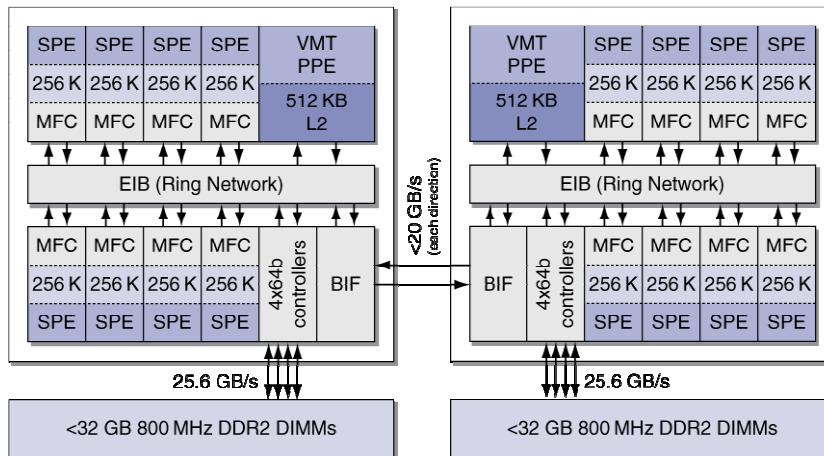
2 × quad-core
AMD Opteron X4 2356
(Barcelona)



Four Example Systems



2 x oct-core
Sun UltraSPARC
T2 5140 (Niagara 2)

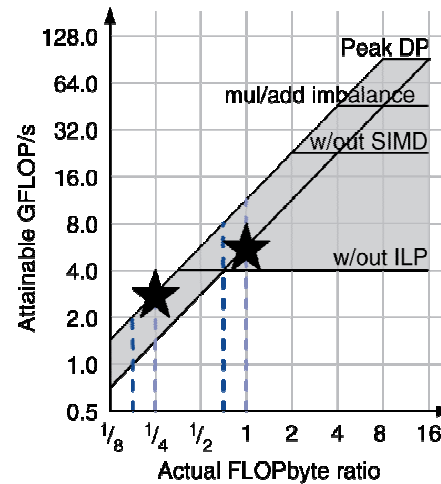


2 x oct-core
IBM Cell QS20

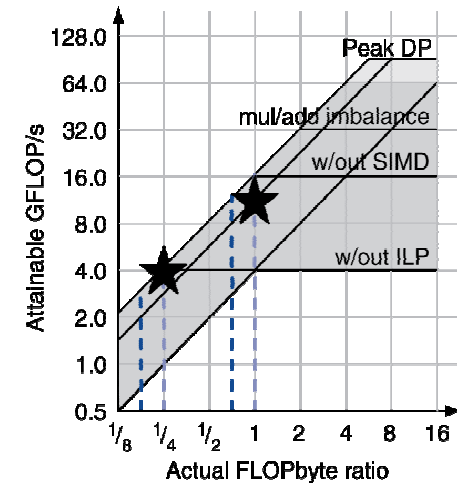


And Their Rooflines

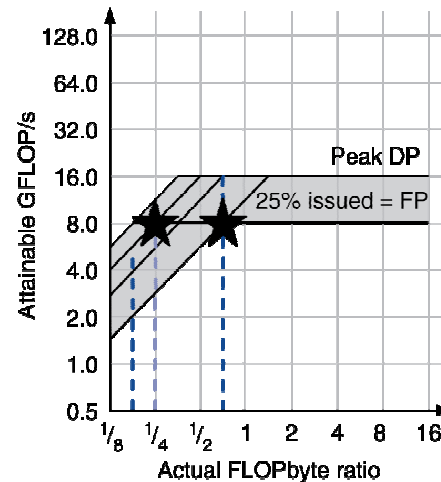
- Kernels
 - SpMV (left)
 - LBHMD (right)
- Some optimizations change arithmetic intensity
- x86 systems have higher peak GFLOPs
 - But harder to achieve, given memory bandwidth



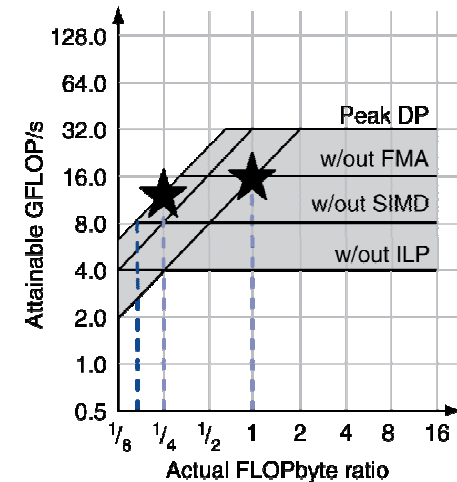
a. Intel Xeon e5345 (Clovertown)



b. AMD Opteron X4 2356 (Barcelona)



c. Sun UltraSPARC T2 5140 (Niagara 2)

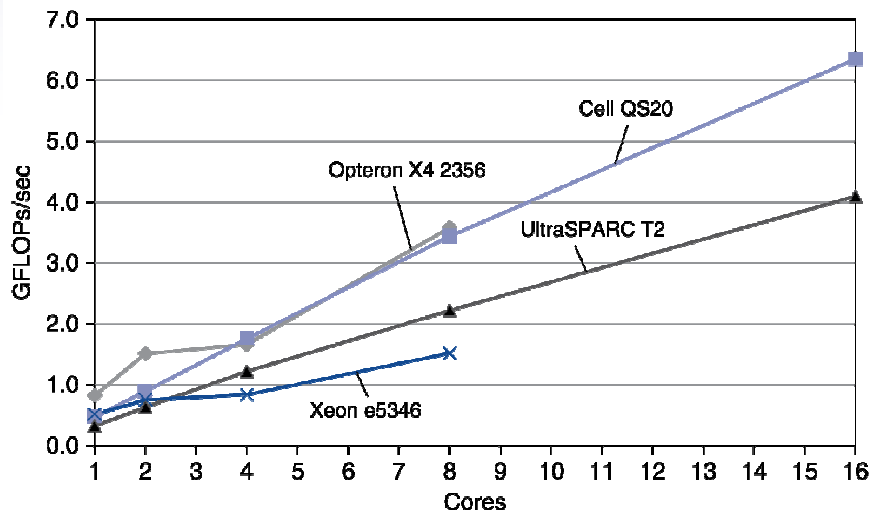


d. IBM Cell QS20



Performance on SpMV

- Sparse matrix/vector multiply
 - Irregular memory accesses, memory bound
- Arithmetic intensity
 - 0.166 before memory optimization, 0.25 after

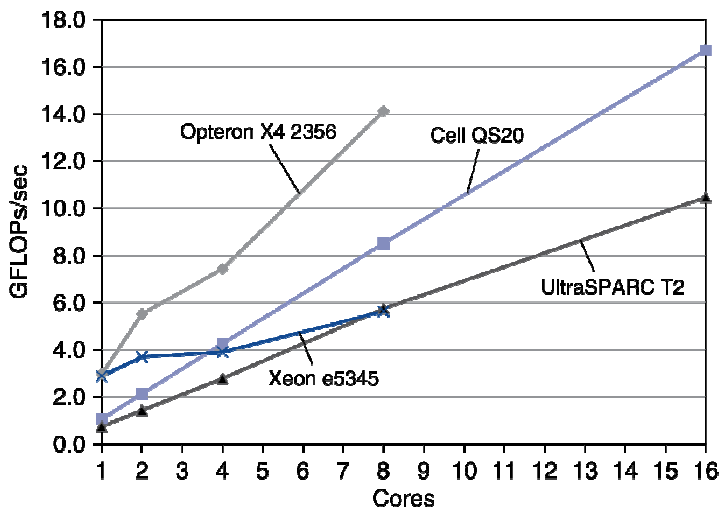


- Xeon vs. Opteron
 - Similar peak FLOPS
 - Xeon limited by shared FSBs and chipset
- UltraSPARC/Cell vs. x86
 - 20 – 30 vs. 75 peak GFLOPs
 - More cores and memory bandwidth



Performance on LBMHD

- Fluid dynamics: structured grid over time steps
 - Each point: 75 FP read/write, 1300 FP ops
- Arithmetic intensity
 - 0.70 before optimization, 1.07 after



- Opteron vs. UltraSPARC
 - More powerful cores, not limited by memory bandwidth
- Xeon vs. others
 - Still suffers from memory bottlenecks



Achieving Performance

- Compare naïve vs. optimized code
 - If naïve code performs well, it's easier to write high performance code for the system

System	Kernel	Naïve GFLOPs/sec	Optimized GFLOPs/sec	Naïve as % of optimized
Intel Xeon	SpMV	1.0	1.5	64%
	LBMHD	4.6	5.6	82%
AMD Opteron X4	SpMV	1.4	3.6	38%
	LBMHD	7.1	14.1	50%
Sun UltraSPARC T2	SpMV	3.5	4.1	86%
	LBMHD	9.7	10.5	93%
IBM Cell QS20	SpMV	Naïve code not feasible	6.4	0%
	LBMHD	Naïve code not feasible	16.7	0%



Fallacies

- Amdahl's Law doesn't apply to parallel computers
 - Since we can achieve linear speedup
 - But only on applications with weak scaling
- Peak performance tracks observed performance
 - Marketers like this approach!
 - But compare Xeon with others in example
 - Need to be aware of bottlenecks



Pitfalls

- Not developing the software to take account of a multiprocessor architecture
 - Example: using a single lock for a shared composite resource
 - Serializes accesses, even if they could be done in parallel
 - Use finer-granularity locking

Concluding Remarks

- Goal: higher performance by using multiple processors
- Difficulties
 - Developing parallel software
 - Devising appropriate architectures
- Many reasons for optimism
 - Changing software and application environment
 - Chip-level multiprocessors with lower latency, higher bandwidth interconnect
- An ongoing challenge for computer architects!

