Parallel programming: Introduction to GPU architecture

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PPAR - 2018

Outline of the course

- March 6: Introduction to GPU architecture
  - Parallelism and how to exploit it
  - Performance models
- March 13: GPU programming
  - The software side
  - Programming model
- March 20: Performance optimization
  - Possible bottlenecks
  - Common optimization techniques
- 4 lab sessions, starting March 14-15
  - Labs 1&2: computing log(2) the hard way
  - Labs 3&4: Conway's Game of Life

Graphics processing unit (GPU)

or

- Graphics rendering accelerator for computer games
  - Mass market: low unit price, amortized R&D
  - Increasing programmability and flexibility
- Inexpensive, high-performance parallel processor
  - GPUs are everywhere, from cell phones to supercomputers
- General-Purpose computation on GPU (GPGPU)

GPUs in high-performance computing

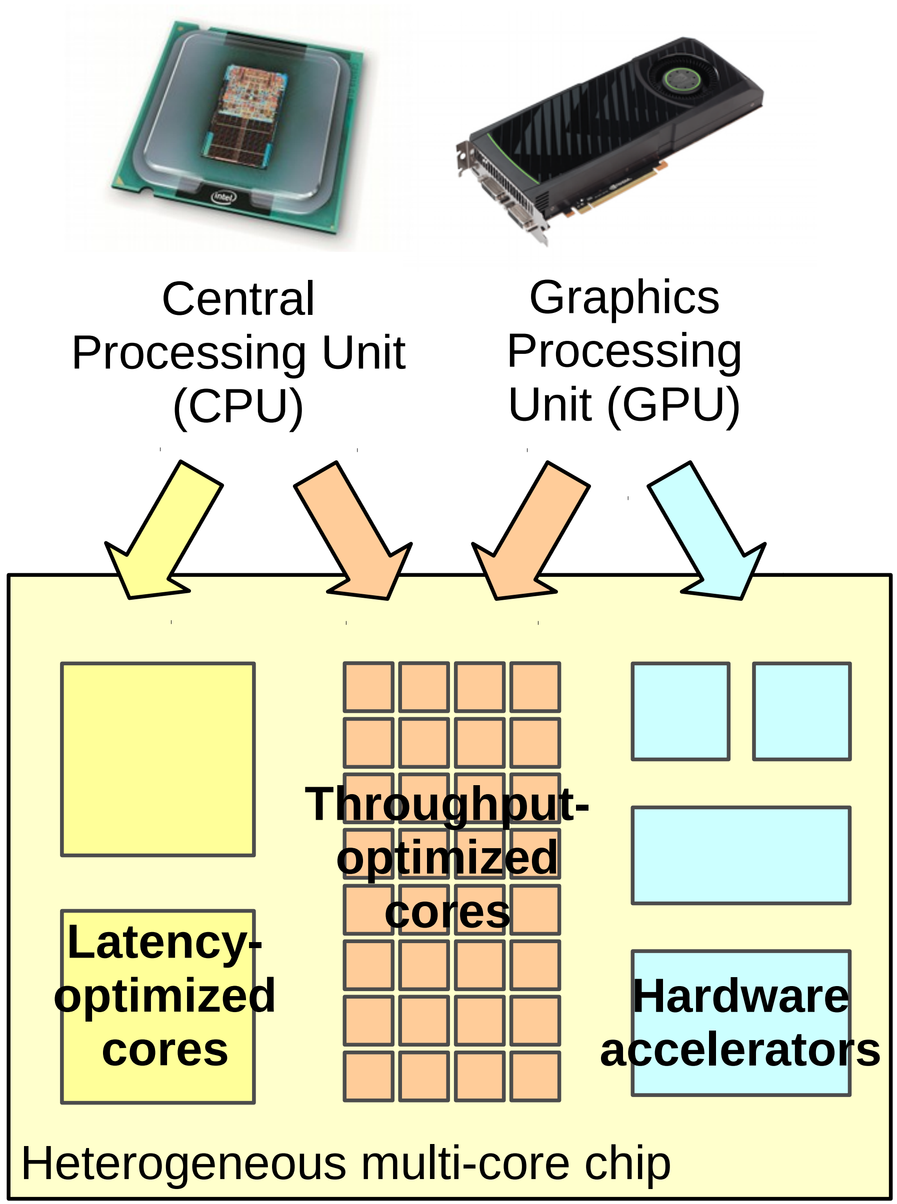
- GPU/accelerator share in Top500 supercomputers
  - In 2010: 2%
  - In 2016: 17%
- 2016+ trend:
  Heterogeneous multi-core processors influenced by GPUs

#1 Sunway TaihuLight (China)
40,960 × SW26010 (4 big + 256 small cores)

#2 Tianhe-2 (China)
16,000 × (2×12-core Xeon + 3×57-core Xeon Phi)

GPGPU in the future?

- Yesterday (2000-2010)
  - Homogeneous multi-core
  - Discrete components
- Today (2011-...)
  Chip-level integration
  - Many embedded SoCs
  - Intel Sandy Bridge
  - AMD Fusion
  - NVIDIA Denver/Maxwell project…
- Tomorrow
  Heterogeneous multi-core
  - GPUs to blend into throughput-optimized cores?



Outline

- GPU, many-core: why, what for?
  - Technological trends and constraints
  - From graphics to general purpose
- Forms of parallelism, how to exploit them
  - Why we need (so much) parallelism: latency and throughput
  - Sources of parallelism: ILP, TLP, DLP
  - Uses of parallelism: horizontal, vertical
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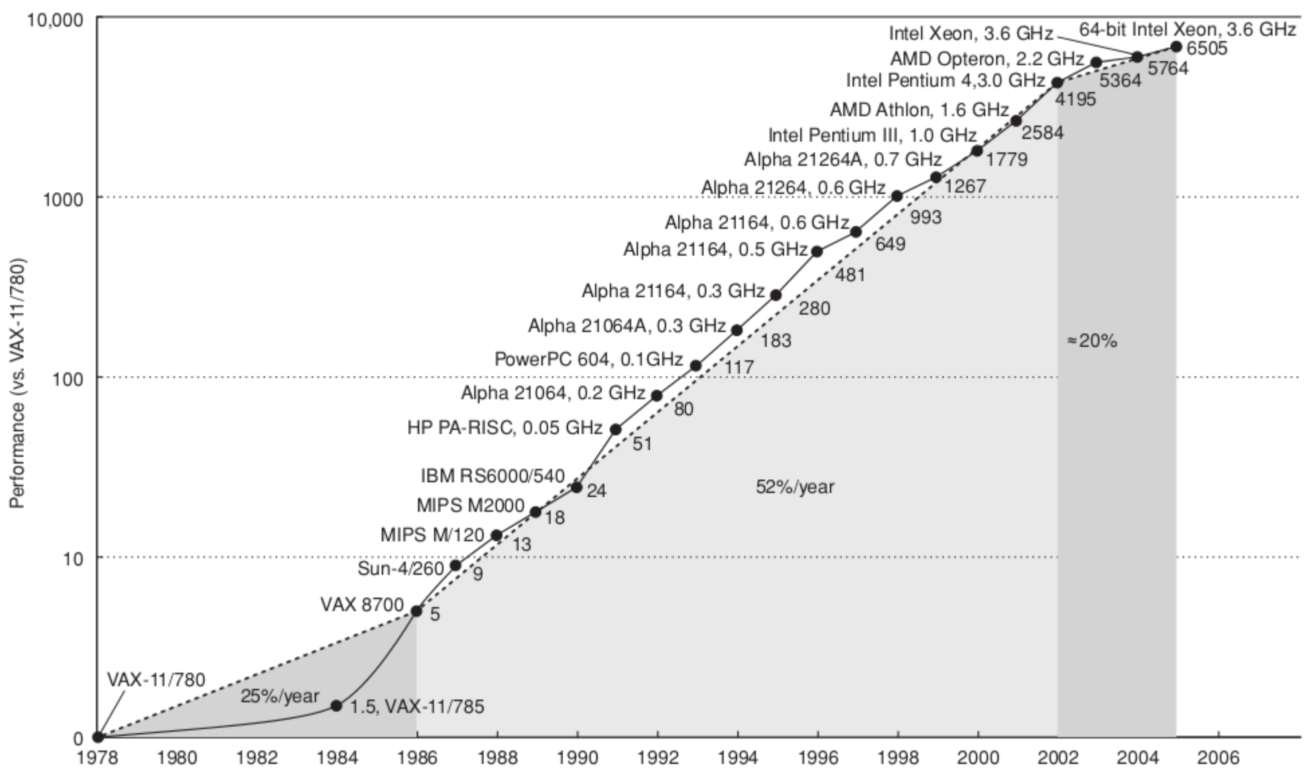
  - Ingredients: Sequential core, Multi-core, Multi-threaded core, SIMD
  - Putting it all together
  - Architecture of current GPUs: cores, memory
- High-level performance modeling

The free lunch era... was yesterday

- 1980's to 2002: *Moore's law*, *Dennard scaling*, micro-architecture improvements
  - Exponential performance increase
  - Software compatibility preserved

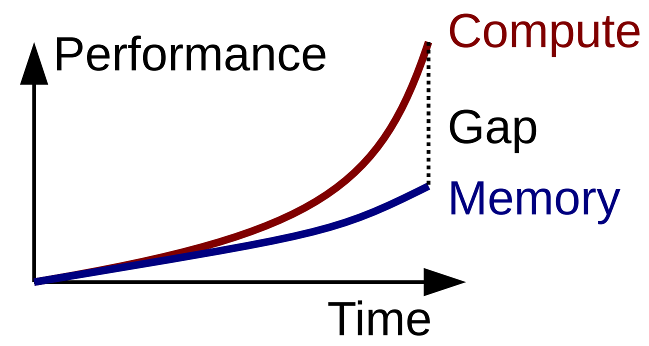


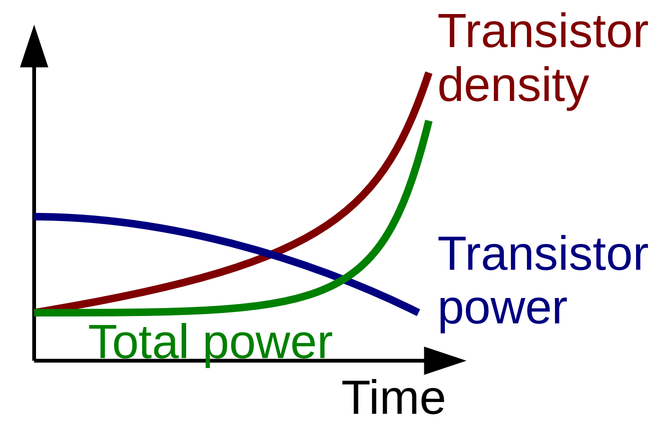
Hennessy, Patterson. Computer Architecture, a quantitative approach. 4th Ed. 2006

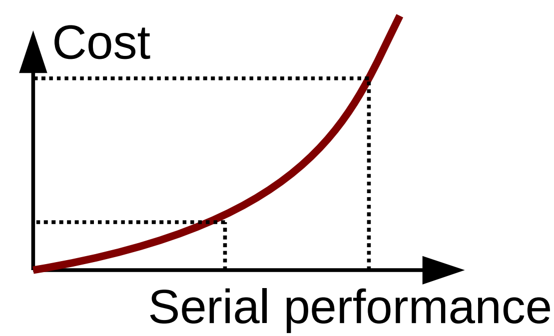
- Do not rewrite software, buy a new machine!

Technology evolution

- Memory wall
  - Memory speed does not increase as fast as computing speed
  - Harder to hide memory latency
- Power wall
  - Power consumption of transistors does not decrease as fast as density increases
  - Performance is now limited by power consumption
- ILP wall
  - Law of diminishing returns on Instruction-Level Parallelism
  - Pollack rule: cost ≃ performance²







Usage changes

- New applications demand **parallel processing**
  - Computer games : 3D graphics
  - Search engines, social networks… “big data” processing
- New computing devices are **power-constrained**
  - Laptops, cell phones, tablets…
    - Small, light, battery-powered
  - Datacenters
    - High power supply and cooling costs

Latency vs. throughput

- **Latency**: time to solution
  - Minimize time, at the expense of power
  - Metric: time
    e.g. seconds
- **Throughput**: quantity of tasks processed per unit of time
  - Assumes unlimited parallelism
  - Minimize energy per operation
  - Metric: operations / time
    e.g. Gflops / s
- CPU: optimized for latency
- GPU: optimized for throughput

Amdahl's law

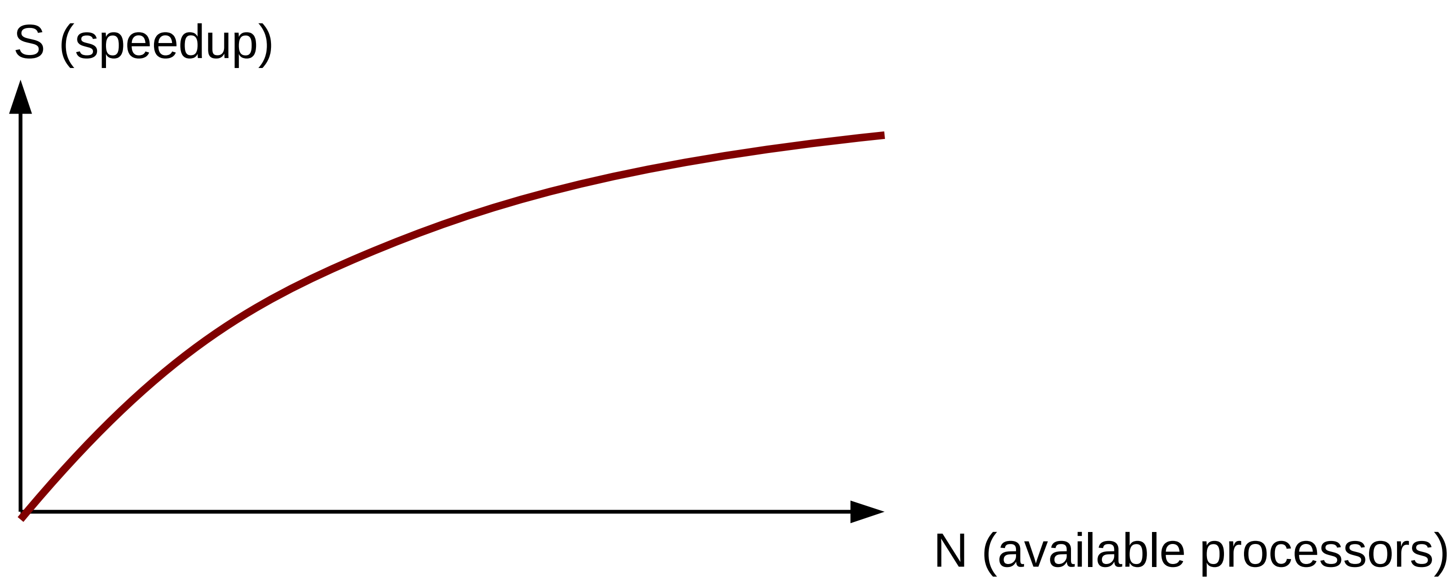
- Bounds speedup attainable on a parallel machine

$$S = \frac{1}{(1-P) + \frac{P}{N}}$$

Time to run sequential portions: $(1-P)$

Time to run parallel portions: $\frac{P}{N}$

S	Speedup
P	Ratio of parallel portions
N	Number of processors



G. Amdahl. Validity of the Single Processor Approach to Achieving Large-Scale Computing Capabilities. AFIPS 1967.

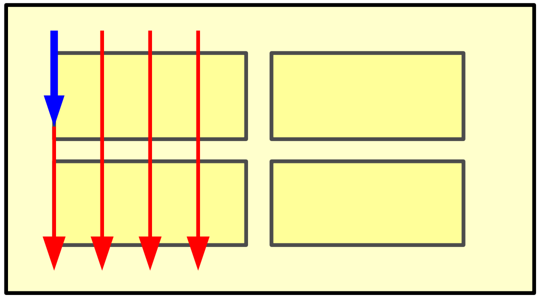
Why heterogeneous architectures?

Time to run sequential portions

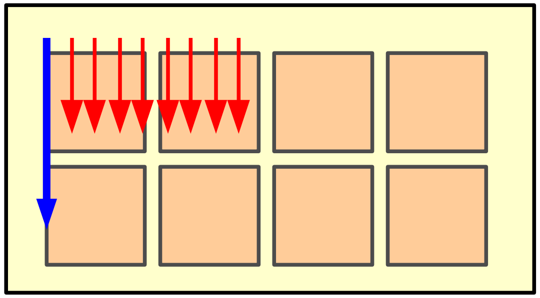
$$S = \frac{1}{(1-P) + \frac{P}{N}}$$

Time to run parallel portions

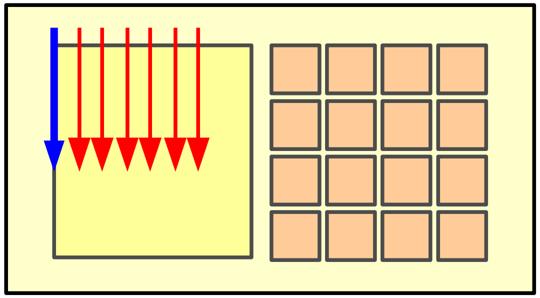
- Latency-optimized multi-core (CPU)
  - Low efficiency on parallel portions: spends too much resources



- Throughput-optimized multi-core (GPU)
  - Low performance on sequential portions

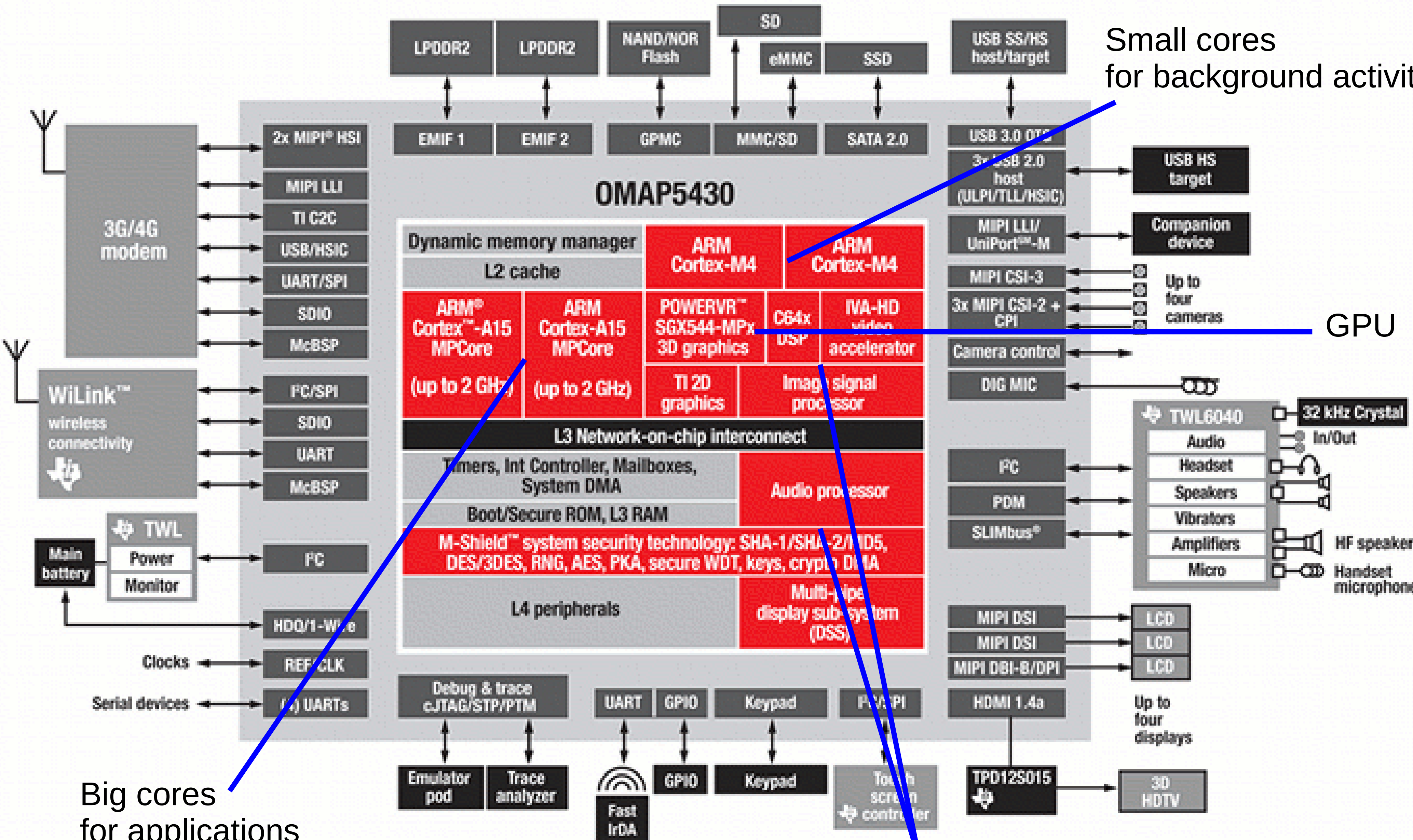


- Heterogeneous multi-core (CPU+GPU)
  - Use the right tool for the right job
  - Allows aggressive optimization for latency **or** for throughput



M. Hill, M. Marty. Amdahl's law in the multicore era. IEEE Computer, 2008.

Example: System on Chip for smartphone



Small cores for background activity

GPU

Big cores for applications

Lots of interfaces

Special-purpose accelerators

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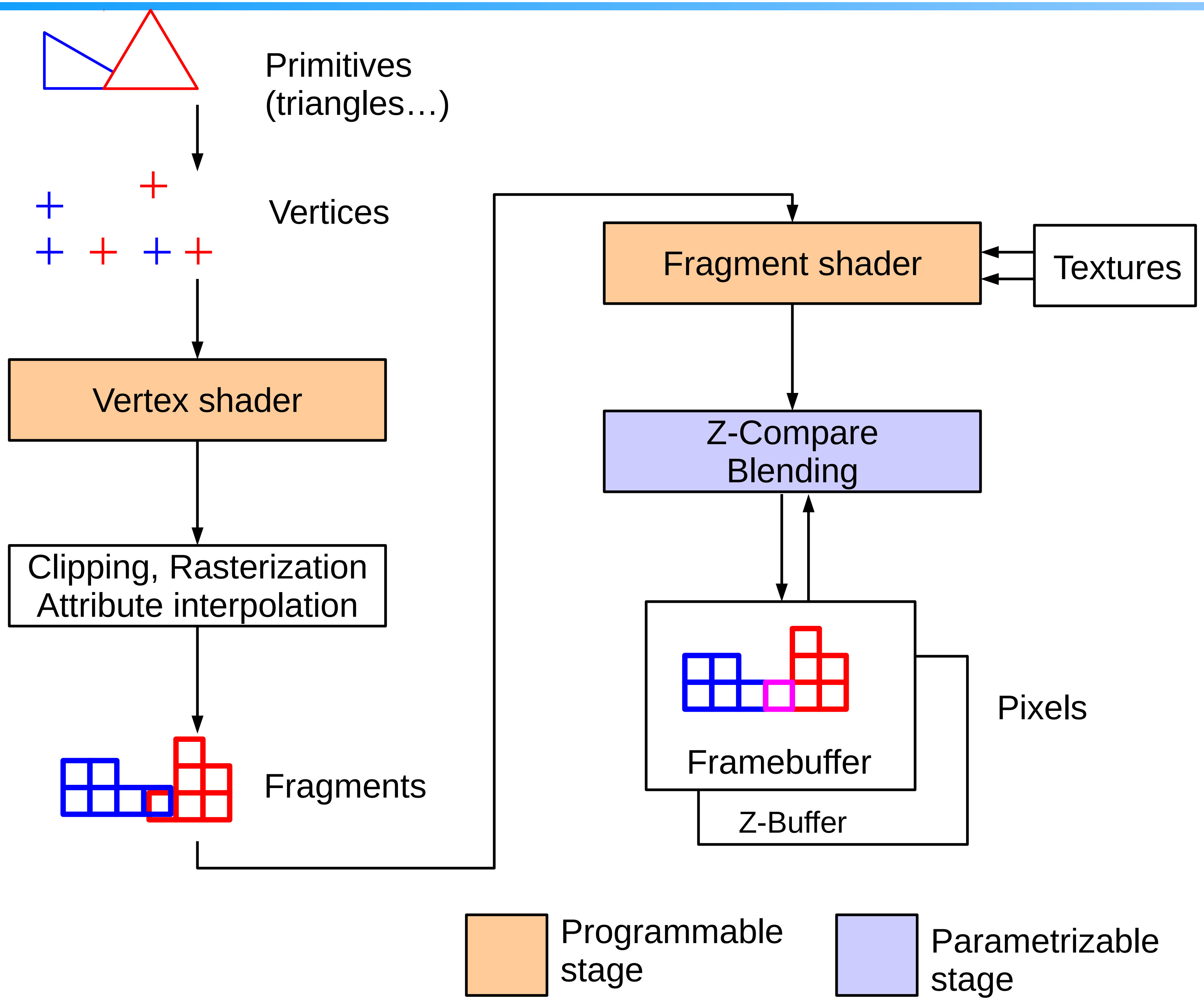
The (simplest) graphics rendering pipeline



How much performance do we need

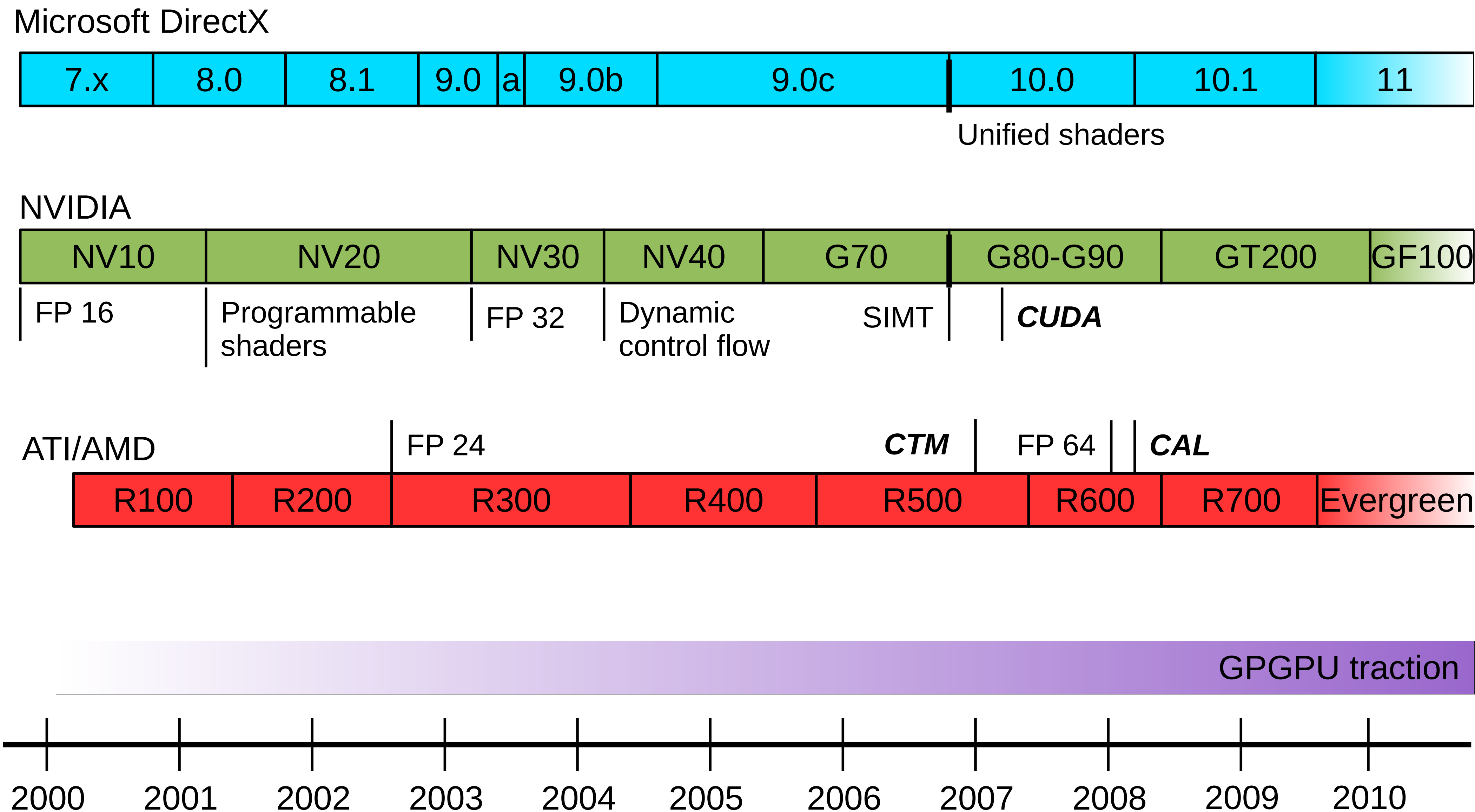
- … to run 3DMark 11 at 50 frames/second?

Element	Per frame	Per second
Vertices	12.0M	600M
Primitives	12.6M	630M
Fragments	180M	9.0G
Instructions	14.4G	**720G**

- Intel Core i7 2700K: 56 Ginsn/s peak
  - We need to go 13x faster
  - Make a special-purpose accelerator

Source: Damien Triolet, Hardware.fr

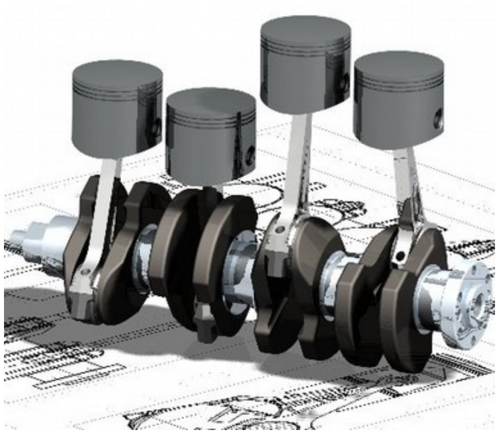
Beginnings of GPGPU



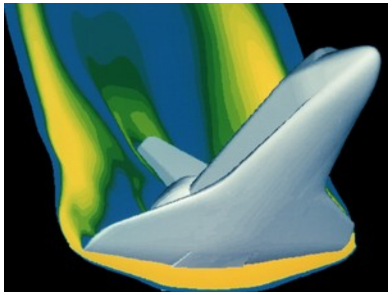
Today: what do we need GPUs for?

1. 3D graphics rendering for games
   - Complex texture mapping, lighting computations…

2. Computer Aided Design workstations
   - Complex geometry



3. GPGPU
   - Complex synchronization, data movements



- One chip to rule them all
  - Find the common denominator

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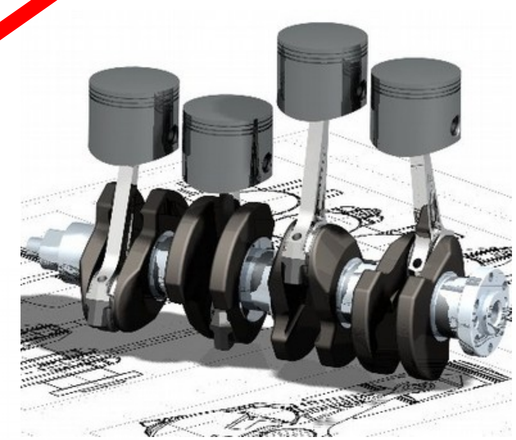

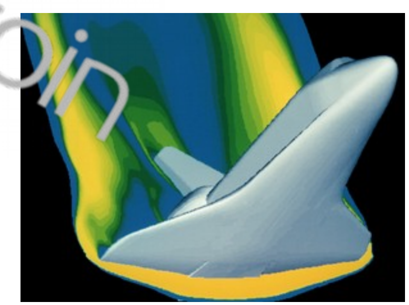

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  - Hardware trends
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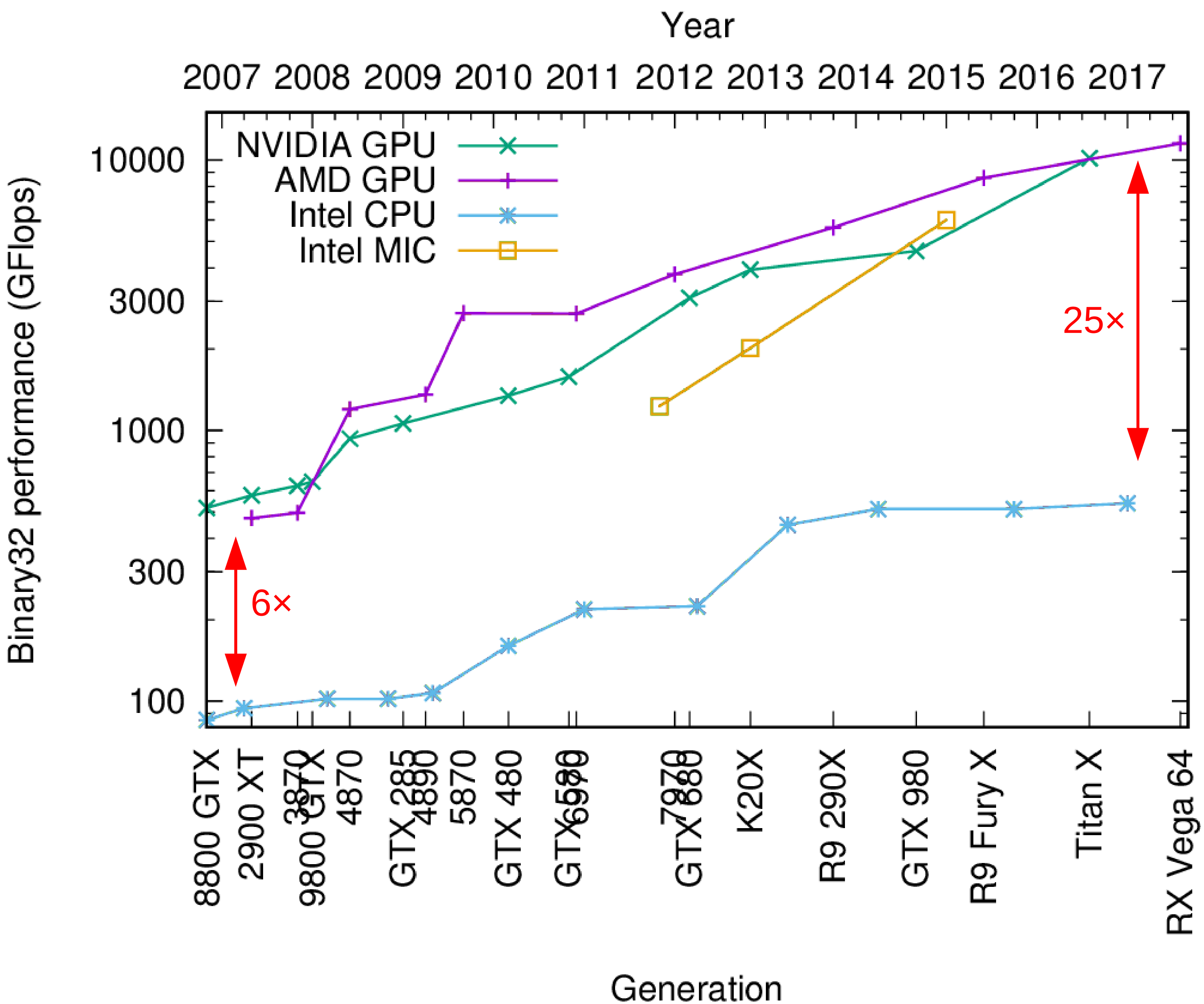
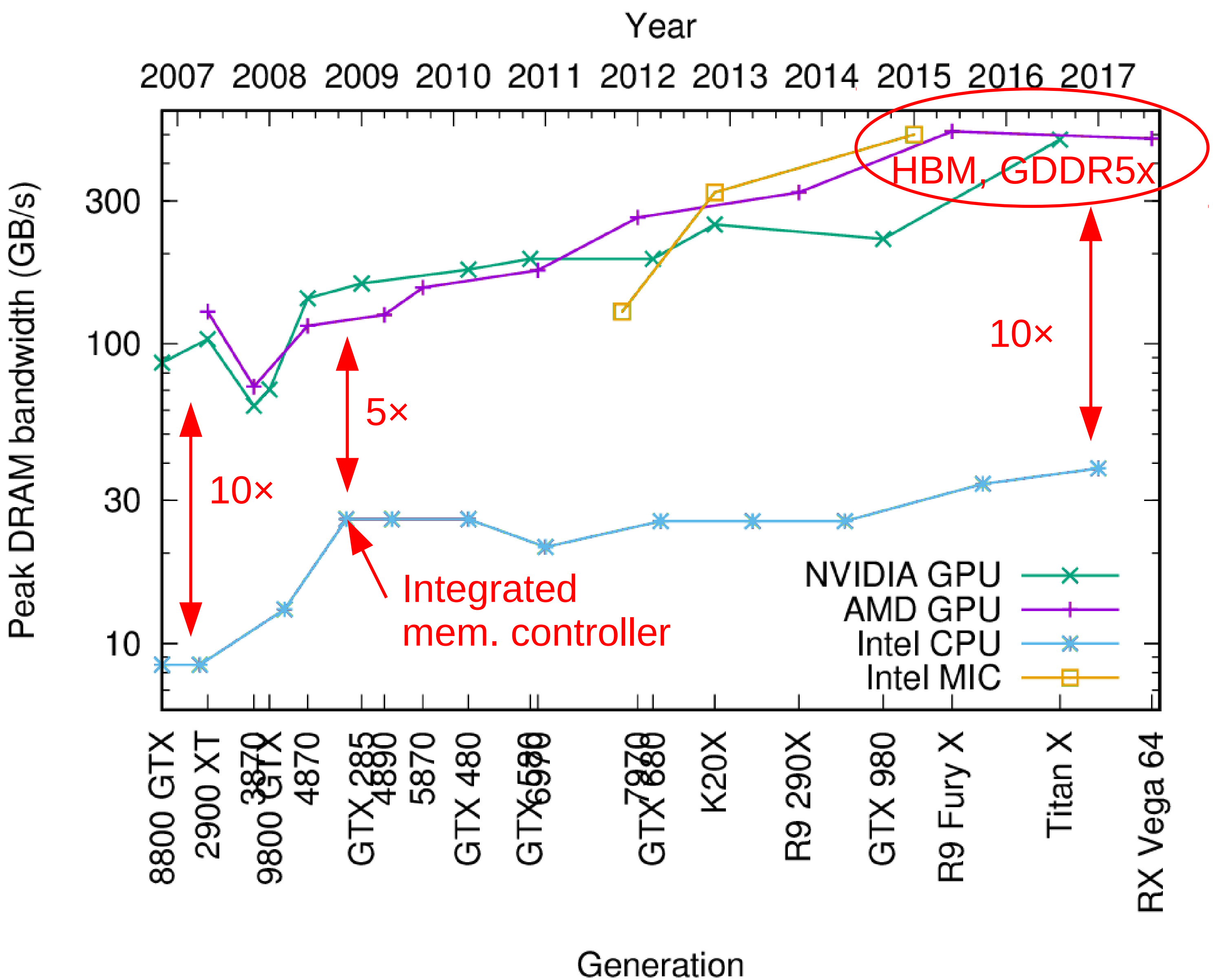
Trends: compute performance

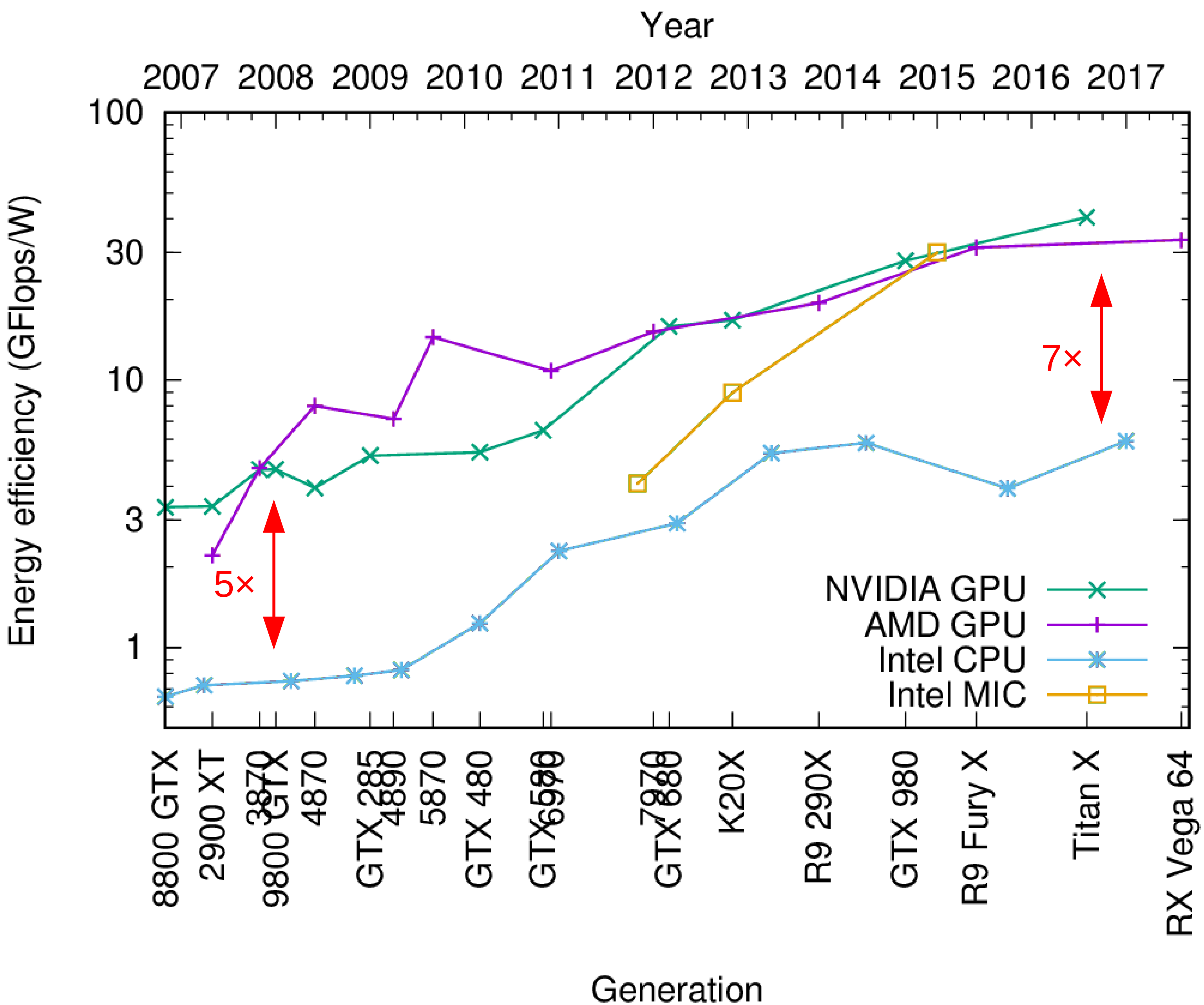


Caveat: only considers **desktop** CPUs. Gap with server CPUs is “only” 4×!

Trends: memory bandwidth



Trends: energy efficiency



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What is parallelism?

Parallelism: independent operations which execution can be overlapped

Operations: memory accesses or computations

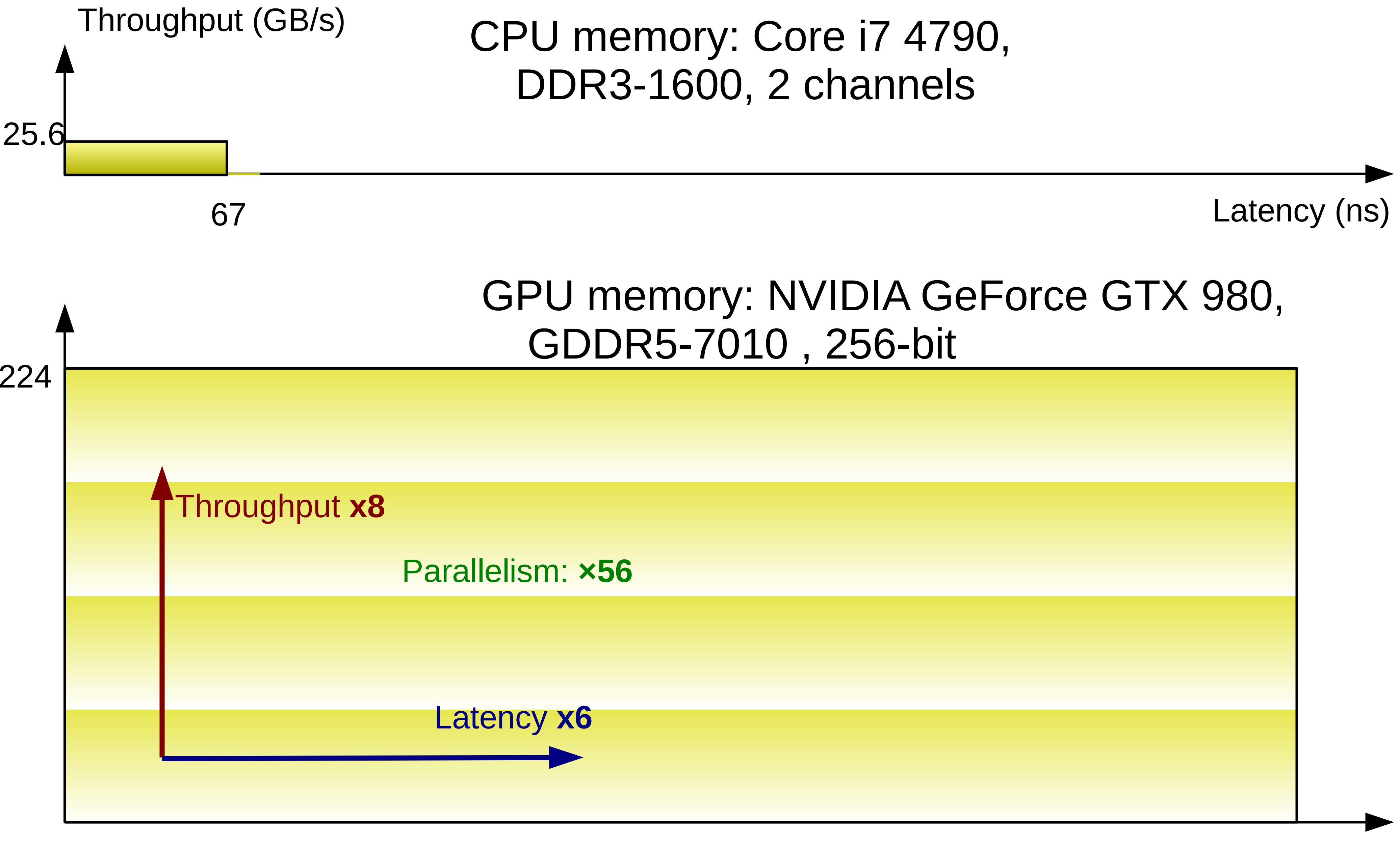
How much parallelism do I need?

- Little's law in queuing theory
  - Average customer arrival rate **λ** ← throughput
  - Average time spent **W** ← latency
  - Average number of customers **L = λ×W** ← **Parallelism** = **throughput** × **latency**

- Units
  - For memory: **B** = **GB/s** × **ns**
  - For arithmetic: **flops** = **Gflops/s** × **ns**

J. Little. A proof for the queuing formula L= λ W. JSTOR 1961.

Throughput and latency: CPU vs. GPU



→ Need 56 times more parallelism!

Sources of parallelism

- ILP: Instruction-Level Parallelism
  - Between independent instructions in sequential program

```
add r3 ← r1, r2
mul r0 ← r0, r1
sub r1 ← r3, r0
```

Parallel

- TLP: Thread-Level Parallelism
  - Between independent execution contexts: threads

Thread 1 Thread 2

add mul Parallel

- DLP: Data-Level Parallelism
  - Between elements of a vector: same operation on several elements

```
vadd r←a,b
```

a_1	a_2	a_3
+	+	+
b_1	b_2	b_3
r_1	r_2	r_3

Example: X ← a×X

- In-place scalar-vector product: X ← a×X

Sequential (ILP)

```
For i = 0 to n-1 do:
    X[i] ← a * X[i]
```

Threads (TLP)

```
Launch n threads:
    X[tid] ← a * X[tid]
```

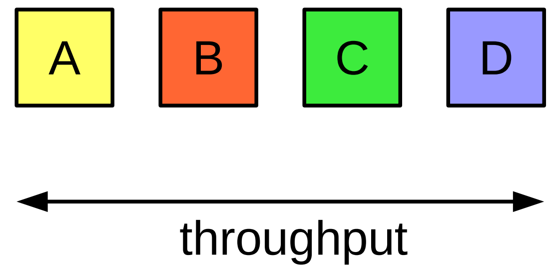
Vector (DLP)

```
    X ← a * X
```

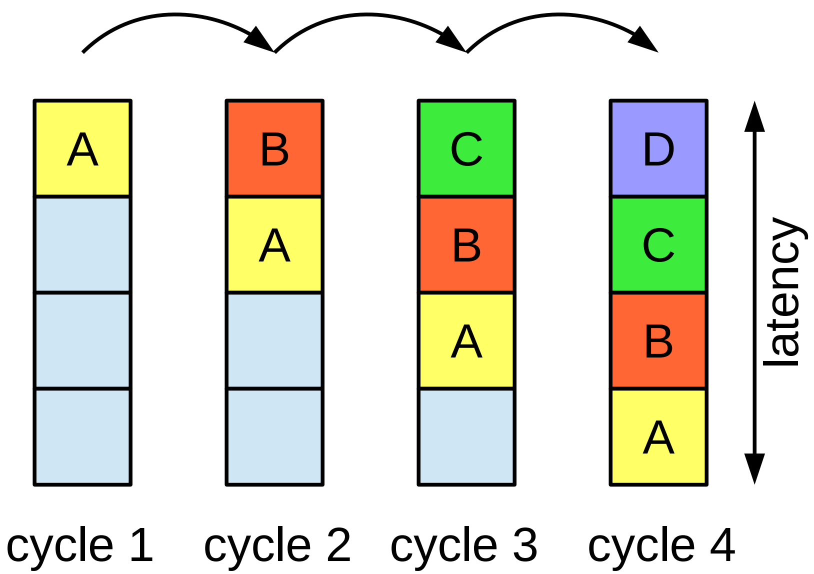
- Or any combination of the above

Uses of parallelism

- “Horizontal” parallelism for throughput
  - More units working in parallel



- “Vertical” parallelism for latency hiding
  - Pipelining: keep units busy when waiting for dependencies, memory



How to extract parallelism?

	Horizontal	Vertical
ILP	Superscalar	Pipelined
TLP	Multi-core SMT	Interleaved / switch-on-event multithreading
DLP	SIMD / SIMT	Vector / temporal SIMT

- We have seen the first row: ILP
- We will now review techniques for the next rows: TLP, DLP

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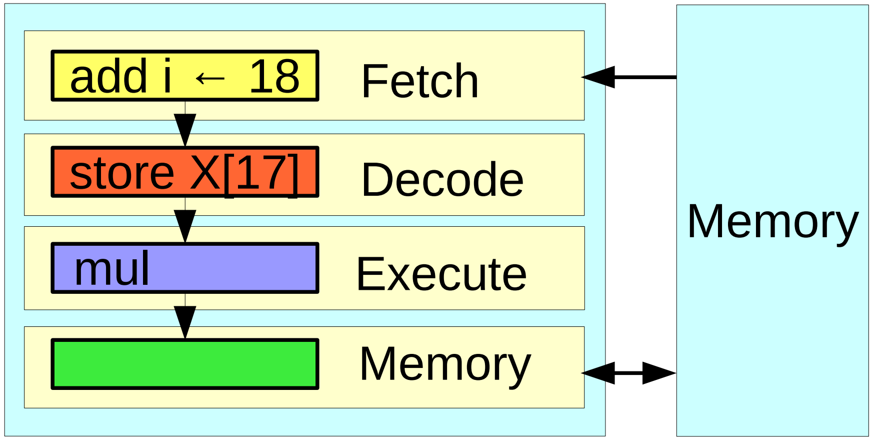
Sequential processor

```
for i = 0 to n-1
   X[i] ← a * X[i]
```

Source code

```
   move   i ← 0
loop:
   load   t ← X[i]
   mul    t ← a×t
   store  X[i] ← t
   add    i ← i+1
   branch i<n? loop
```

Machine code

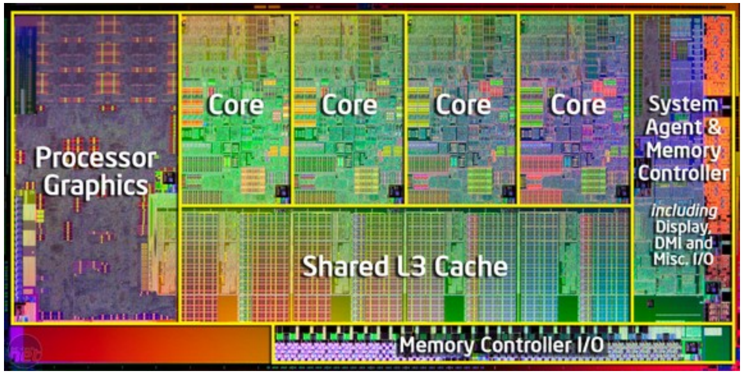


Sequential CPU

- Focuses on instruction-level parallelism
  - Exploits ILP: vertically (pipelining) and horizontally (superscalar)

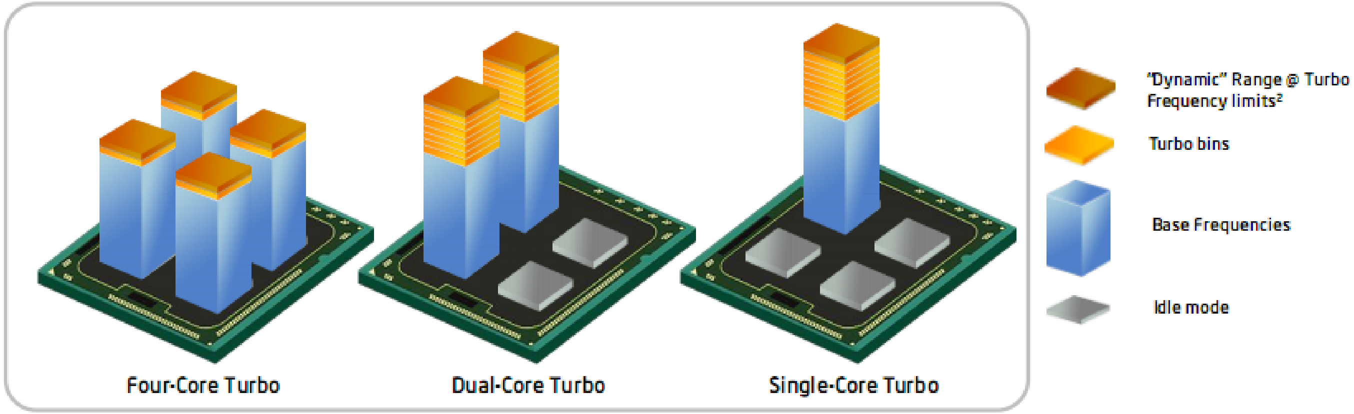
The incremental approach: multi-core

- Several processors
  on a single chip
  sharing one memory space



Intel Sandy Bridge

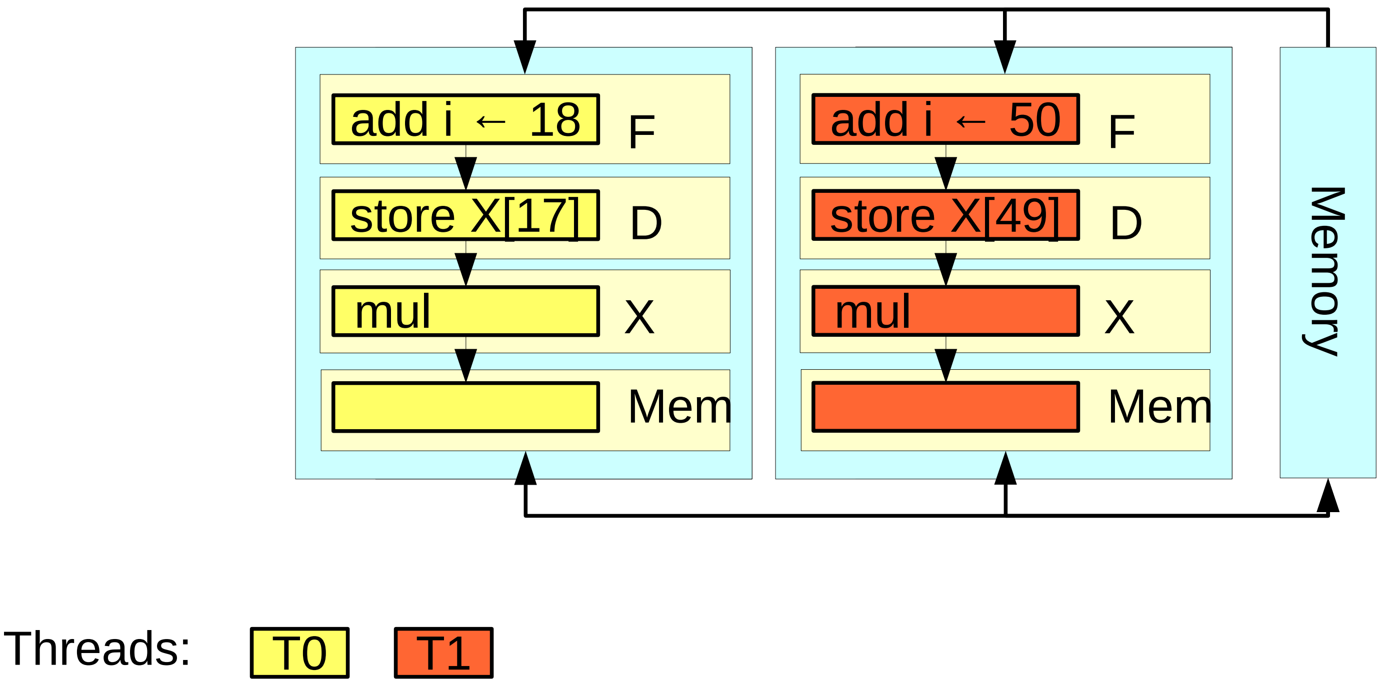
- Area: benefits from Moore's law
- Power: extra cores consume little when not in use
  - e.g. Intel Turbo Boost



Source: Intel

Homogeneous multi-core

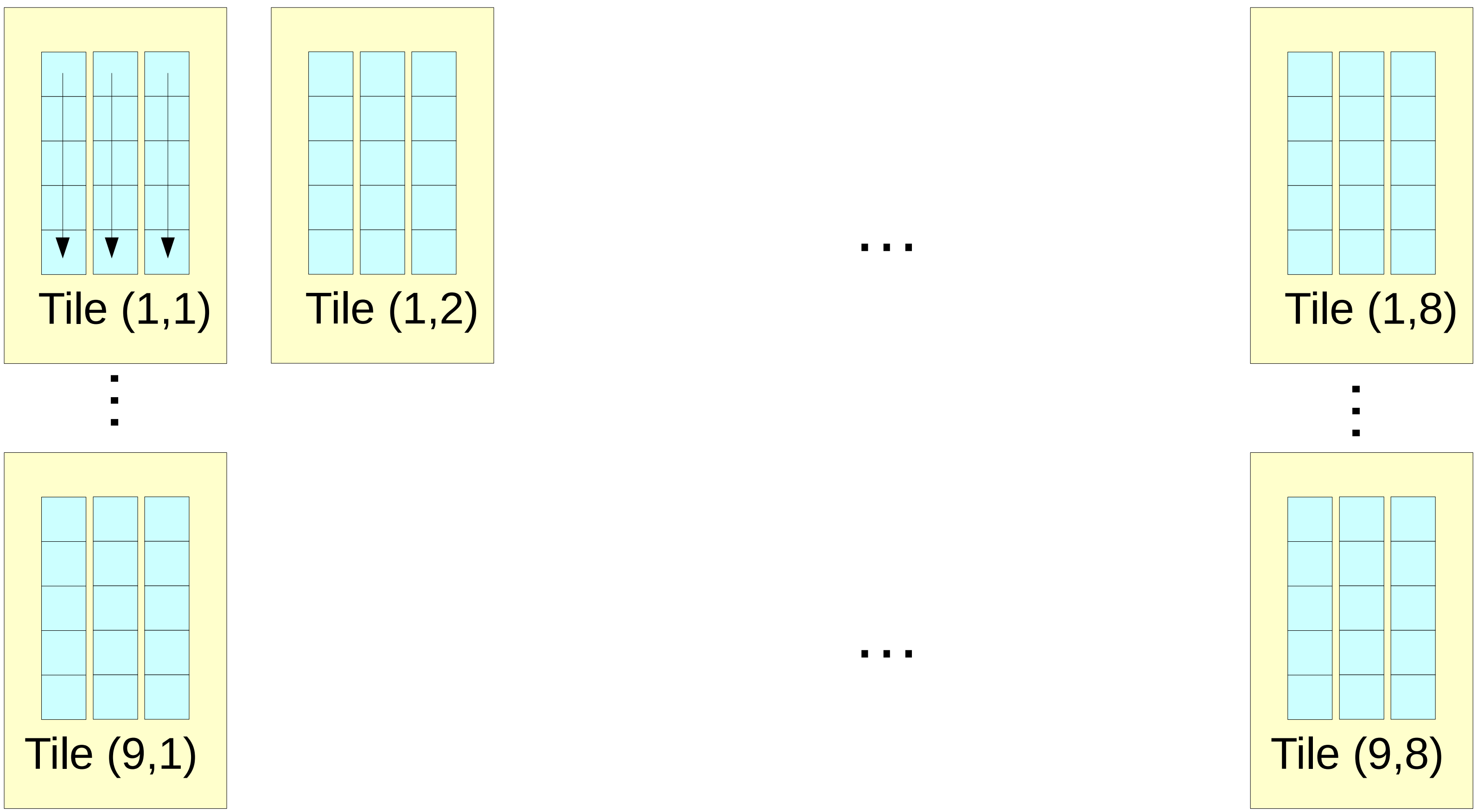
- Horizontal use of thread-level parallelism



- Improves peak throughput

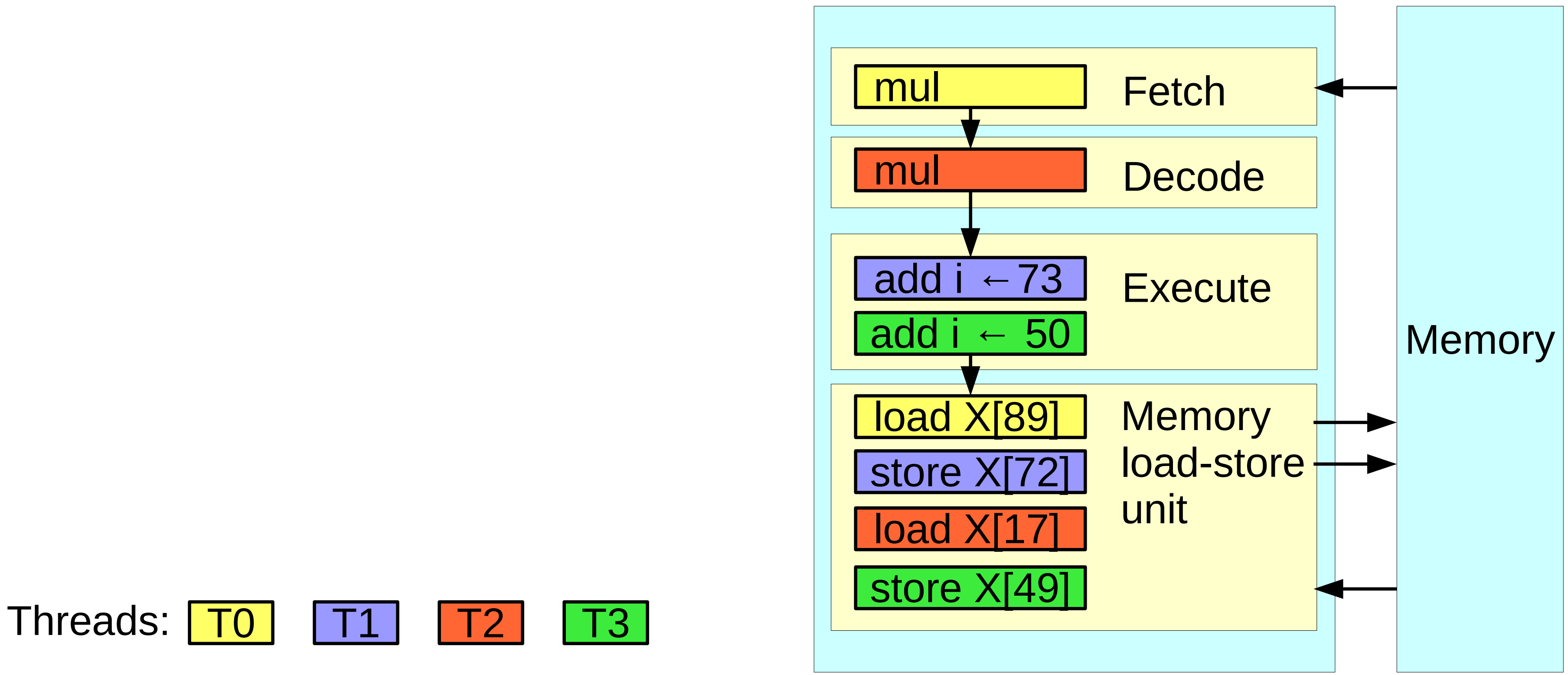
Example: Tilera Tile-GX

- Grid of (up to) 72 tiles
- Each tile: 3-way VLIW processor, 5 pipeline stages, 1.2 GHz



Interleaved multi-threading

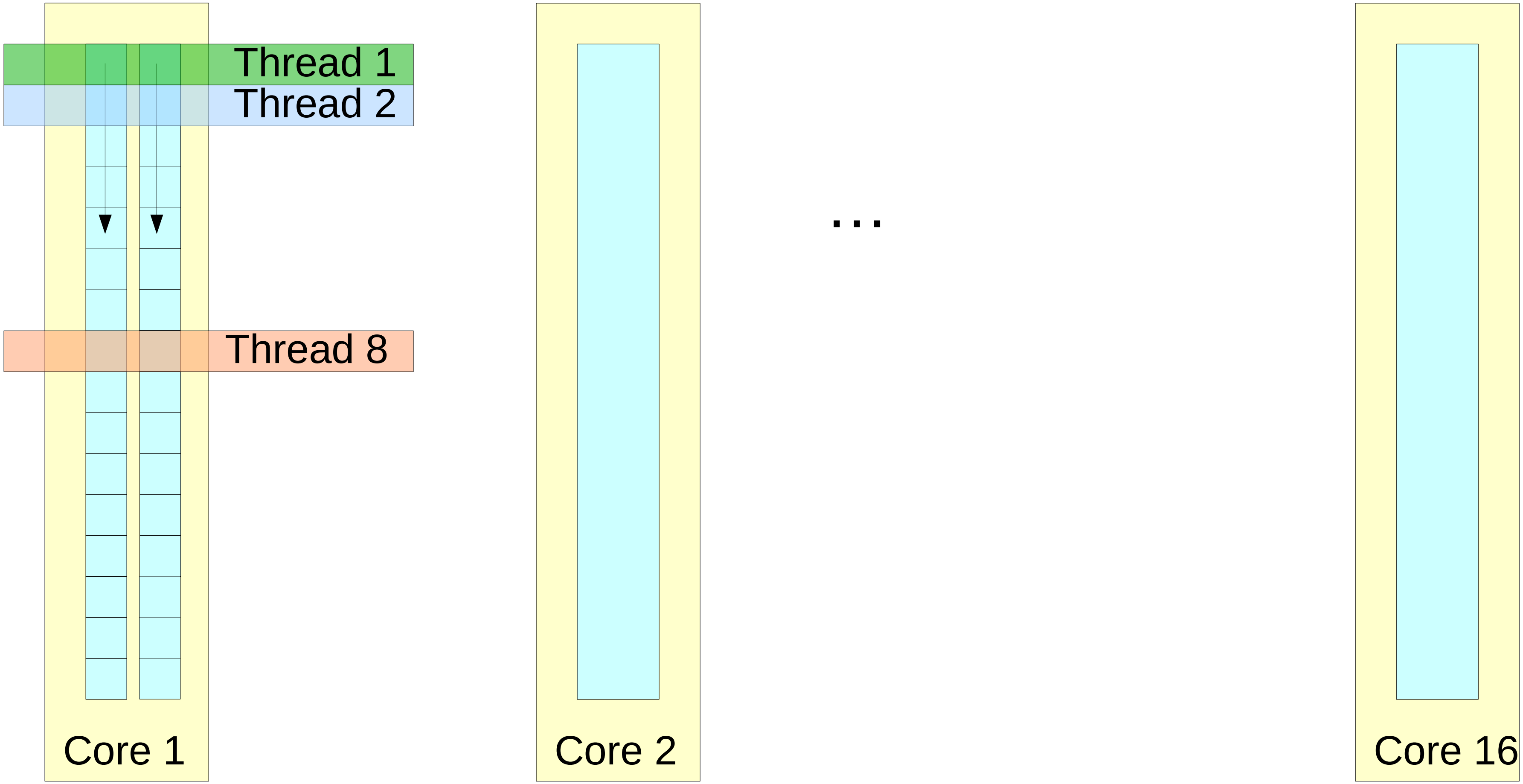
- Vertical use of thread-level parallelism



- Hides latency thanks to explicit parallelism improves achieved throughput

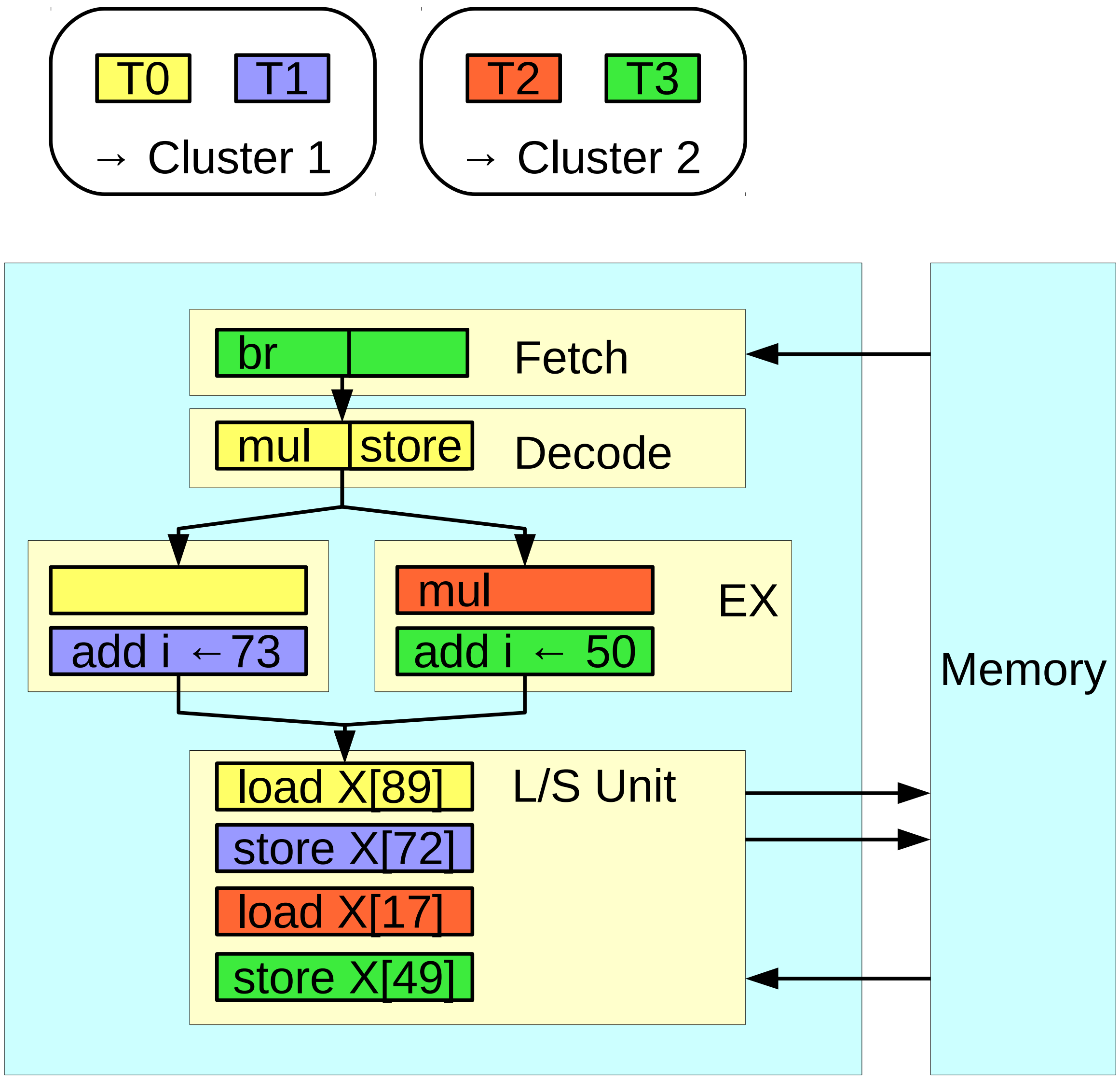
Example: Oracle Sparc T5

- 16 cores / chip
- Core: out-of-order superscalar, 8 threads
- 15 pipeline stages, 3.6 GHz



Clustered multi-core

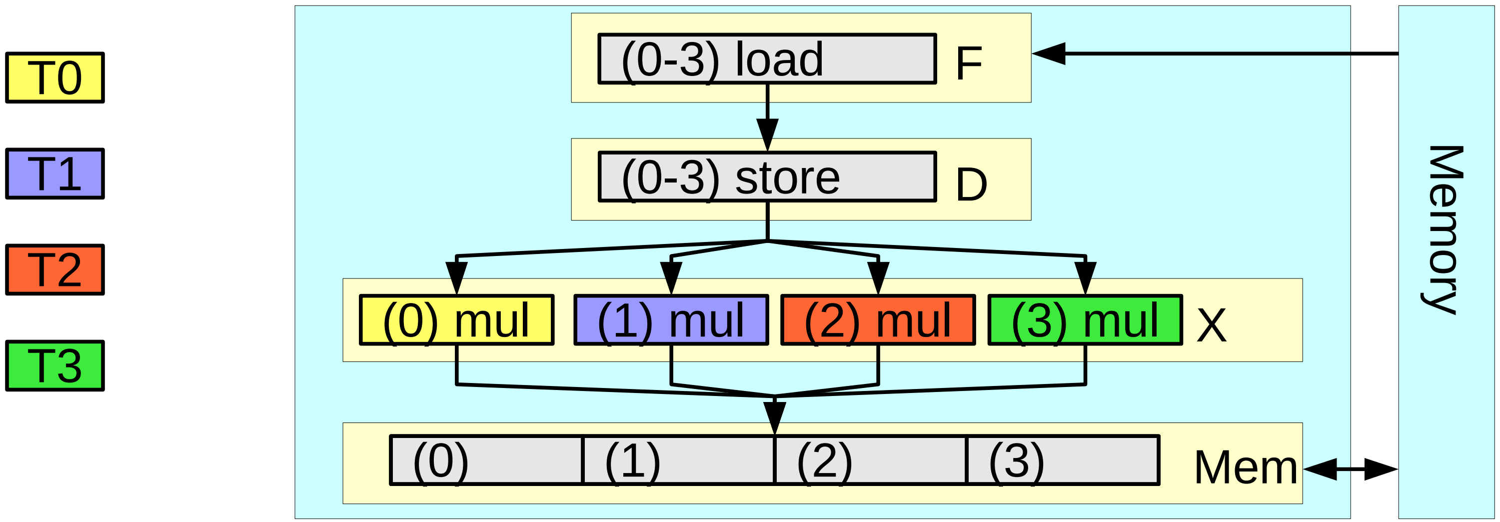
- For each individual unit, select between
  - Horizontal replication
  - Vertical time-multiplexing
- Examples
  - Sun UltraSparc T2, T3
  - AMD Bulldozer
  - IBM Power 7



- Area-efficient tradeoff
- Blurs boundaries between cores

Implicit SIMD

- Factorization of fetch/decode, load-store units
  - Fetch 1 instruction on behalf of several threads
  - Read 1 memory location and broadcast to several registers



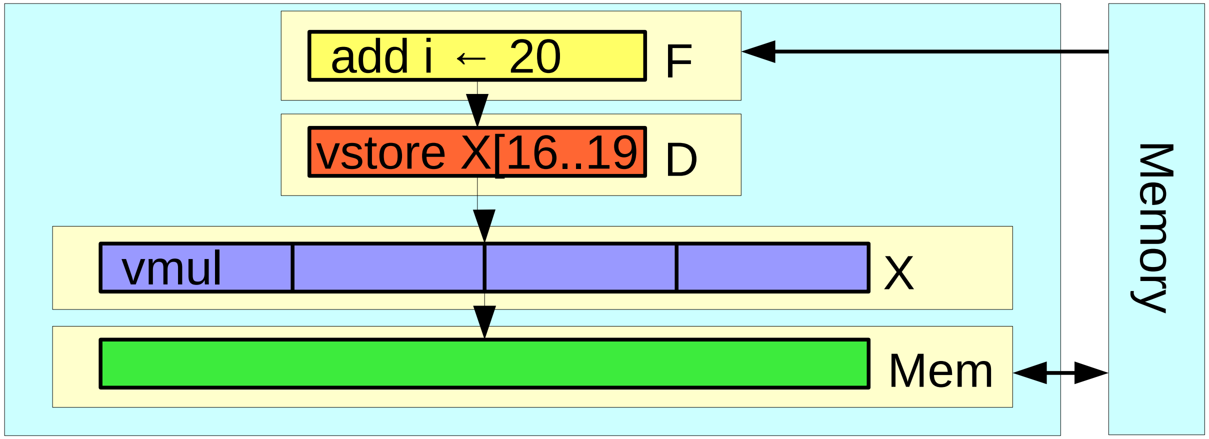
- In NVIDIA-speak
  - SIMT: Single Instruction, Multiple Threads
  - Convoy of synchronized threads: *warp*
- Extracts DLP from multi-thread applications

Explicit SIMD

- Single Instruction Multiple Data
- Horizontal use of data level parallelism

```
loop:
    vload  T ← X[i]
    vmul   T ← a×T
    vstore X[i] ← T
    add    i ← i+4
    branch i<n? loop
```

Machine code



SIMD CPU

- Examples
  - Intel MIC (16-wide)
  - AMD GCN GPU (16-wide×4-deep)
  - Most general purpose CPUs (4-wide to 8-wide)

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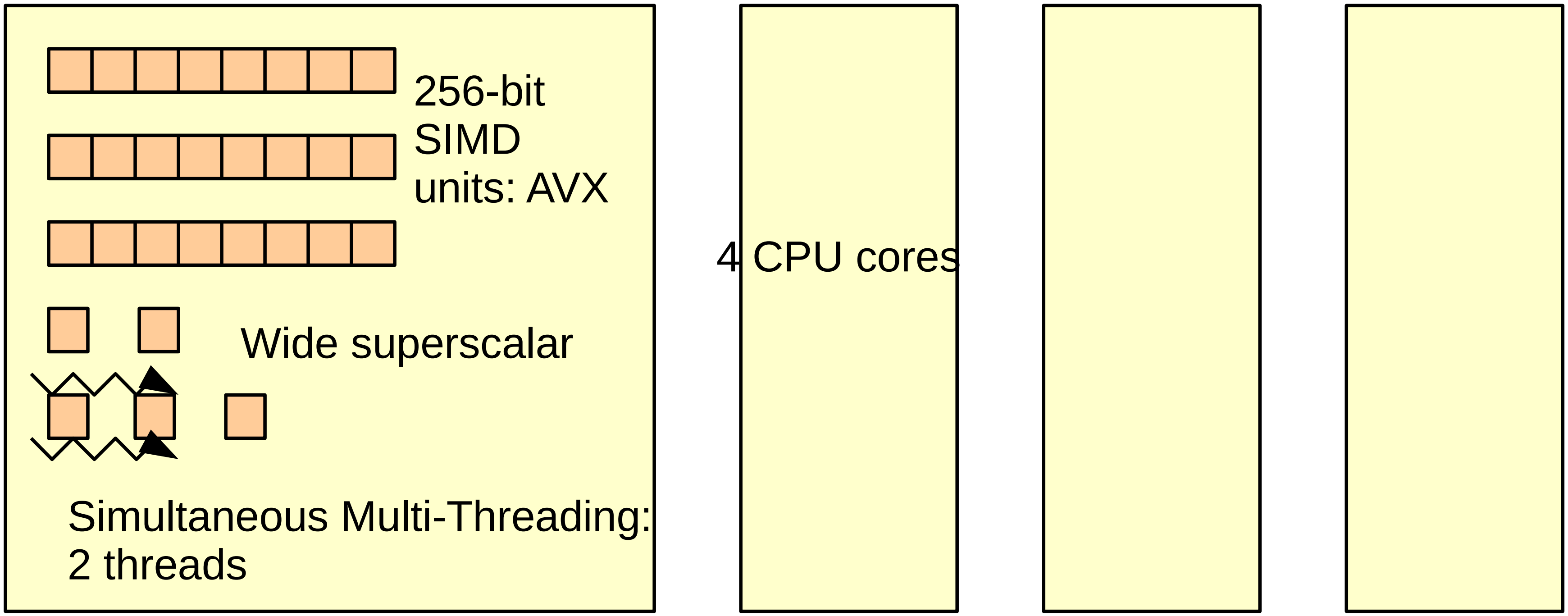
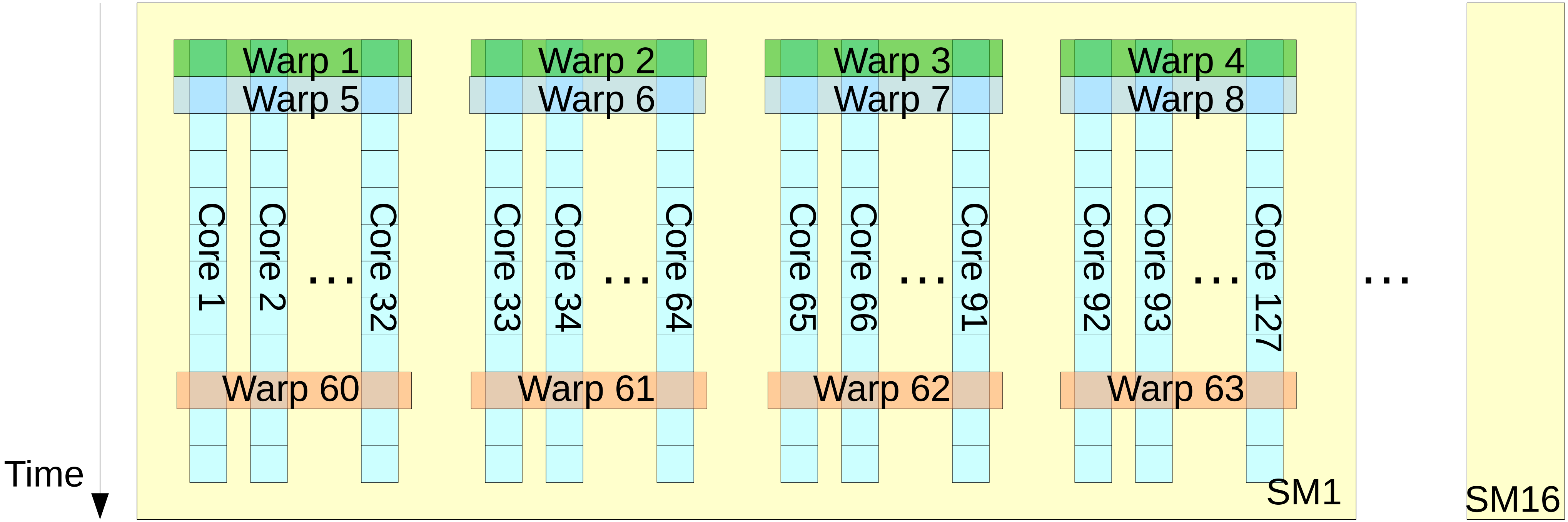
Example CPU: Intel Core i7

- Is a wide superscalar, but has also
  - Multicore
  - Multi-thread / core
  - SIMD units
- Up to 117 operations/cycle from 8 threads



Example GPU: NVIDIA GeForce GTX 980

- SIMT: warps of 32 threads
- 16 SMs / chip
- 4×32 cores / SM, 64 warps / SM

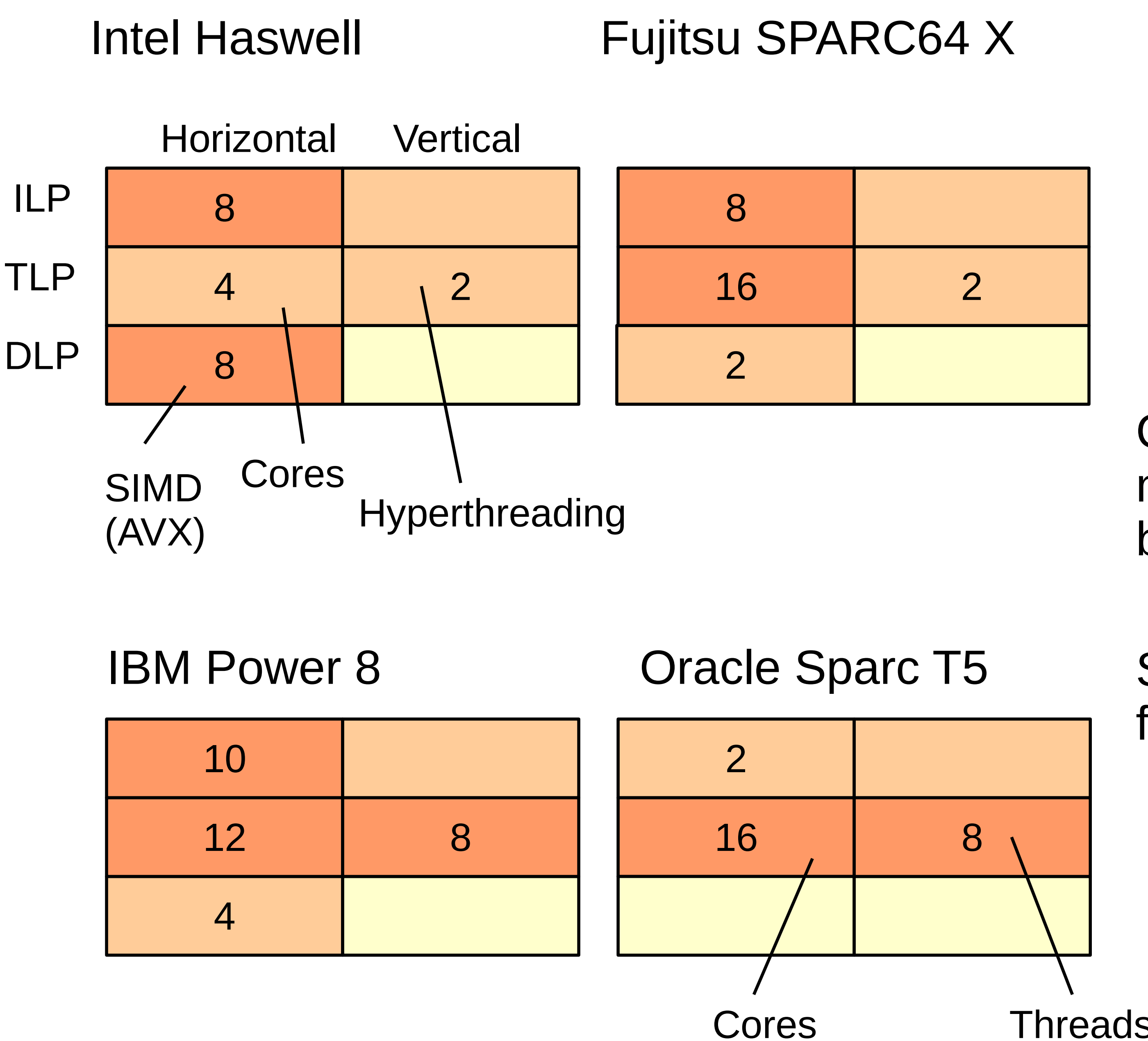


- 4612 Gflop/s
- Up to 32768 threads in flight

Taxonomy of parallel architectures

	Horizontal	Vertical
ILP	Superscalar / VLIW	Pipelined
TLP	Multi-core SMT	Interleaved / switch-on-event multithreading
DLP	SIMD / SIMT	Vector / temporal SIMT

Classification: multi-core



General-purpose multi-cores:
balance ILP, TLP and DLP

Sparc T:
focus on TLP

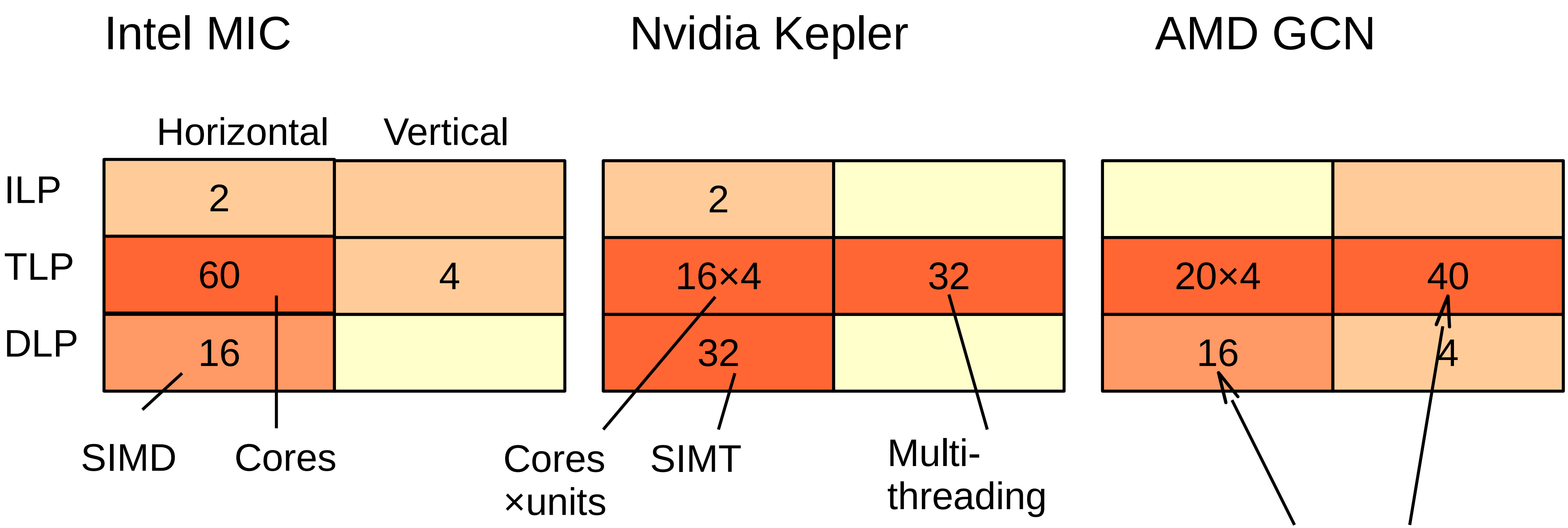
How to read the table

- Given an application with known ILP, TLP, DLP
  how much throughput / latency hiding can I expect?
  - For each cell, take minimum of existing parallelism
    and hardware capability
  - The column-wise product gives throughput / latency hiding

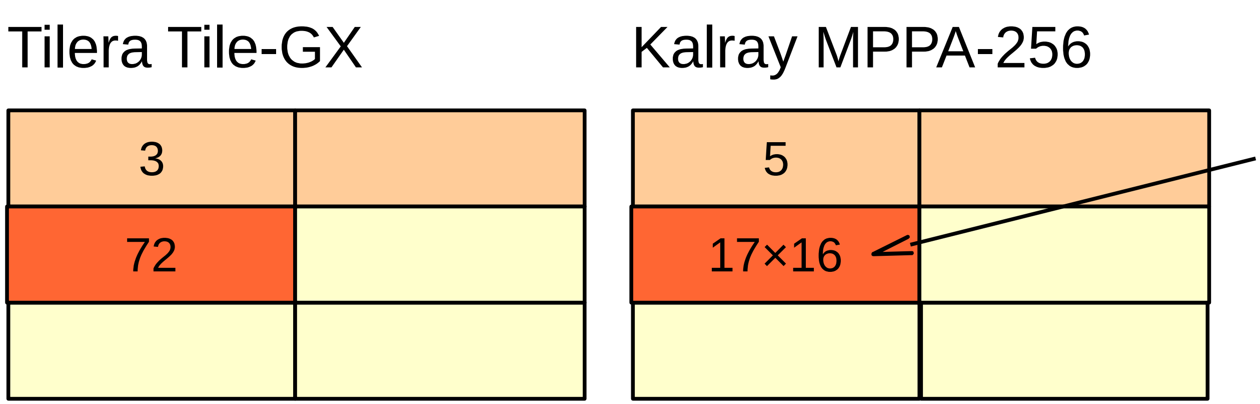
	Sequential code no TLP, no DLP	Horizontal	Vertical
ILP	10	min(8, 10) =8	
TLP	1	min(4, 1)=1	2
DLP	1	min(8, 1)=1	

Max throughput = 8×1×1
for this application
Peak throughput = 8×4×8
→Efficiency: ~3%

Classification: GPU and many small-core



GPU: focus on DLP, TLP horizontal and vertical



Many small-core:
focus on horizontal TLP

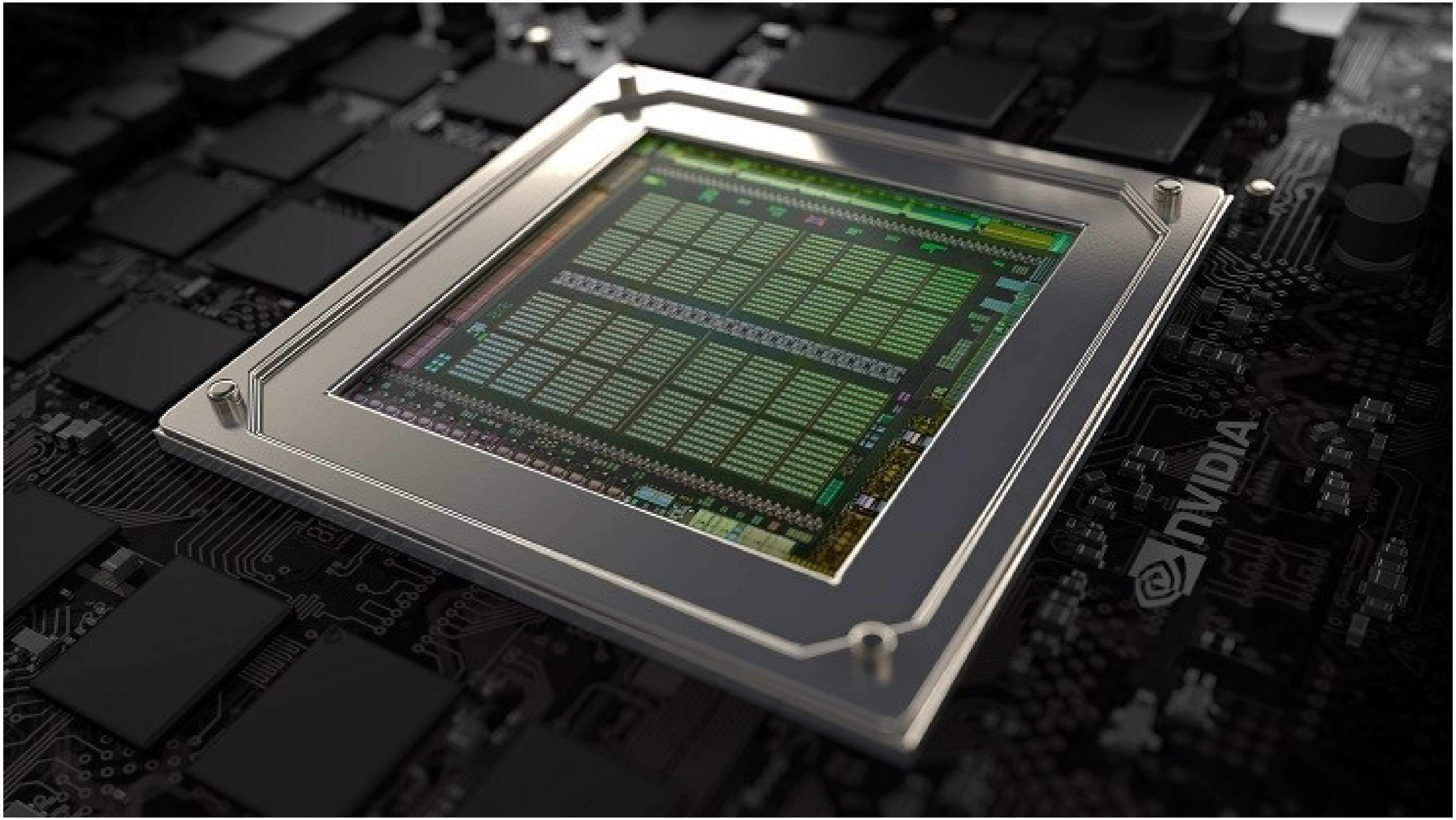
Takeaway

- Parallelism for throughput and latency hiding
- Types of parallelism: ILP, TLP, DLP
- All modern processors exploit the 3 kinds of parallelism
- GPUs focus on Thread-level and Data-level parallelism

Outline

- Computer architecture crash course
  - The simplest processor
  - Exploiting instruction-level parallelism
- GPU, many-core: why, what for?
  - Technological trends and constraints
  - From graphics to general purpose
- Forms of parallelism, how to exploit them
  - Why we need (so much) parallelism: latency and throughput
  - Sources of parallelism: ILP, TLP, DLP
  - Uses of parallelism: horizontal, vertical
- Let's design a GPU!
  - Ingredients: Sequential core, Multi-core, Multi-threaded core, SIMD
  - Putting it all together
  - Architecture of current GPUs: cores, memory

What is inside a graphics card?

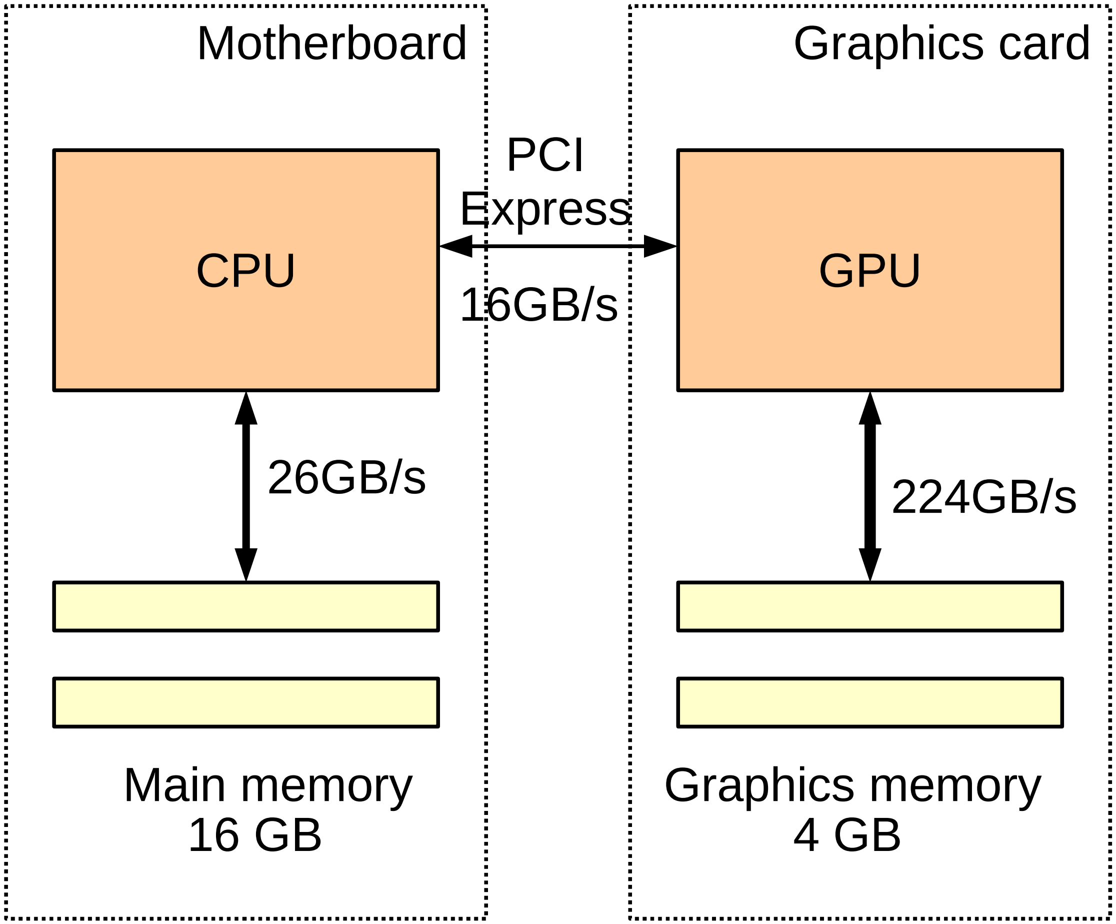


NVIDIA GeForce GTX 980 Maxwell GPU. Artistic rendering!

External memory: discrete GPU

Classical CPU-GPU model

- Split memory spaces
- Need to transfer data explicitly
- Highest bandwidth from GPU memory
- Transfers to main memory are slower



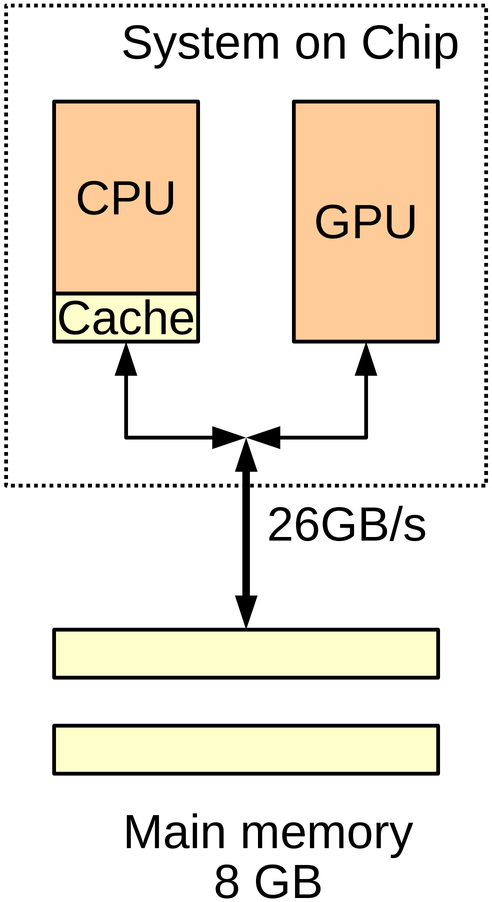
Example configuration:
Intel Core i7 4790, Nvidia GeForce GTX 980

- We will assume this model for CUDA programming

External memory: embedded GPU

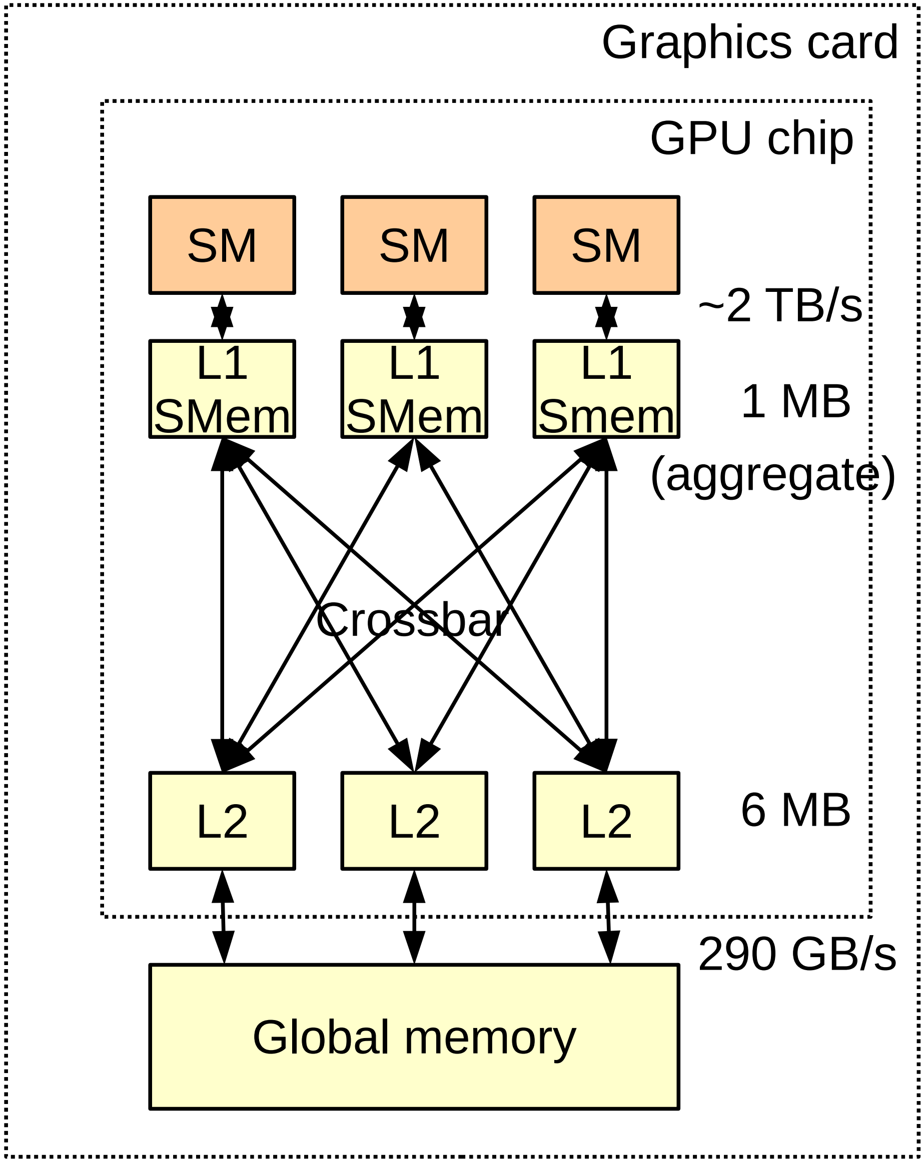
Most GPUs today are integrated

- Same physical memory
- May support memory coherence
  - GPU can read directly from CPU caches
- More contention on external memory



GPU high-level organization

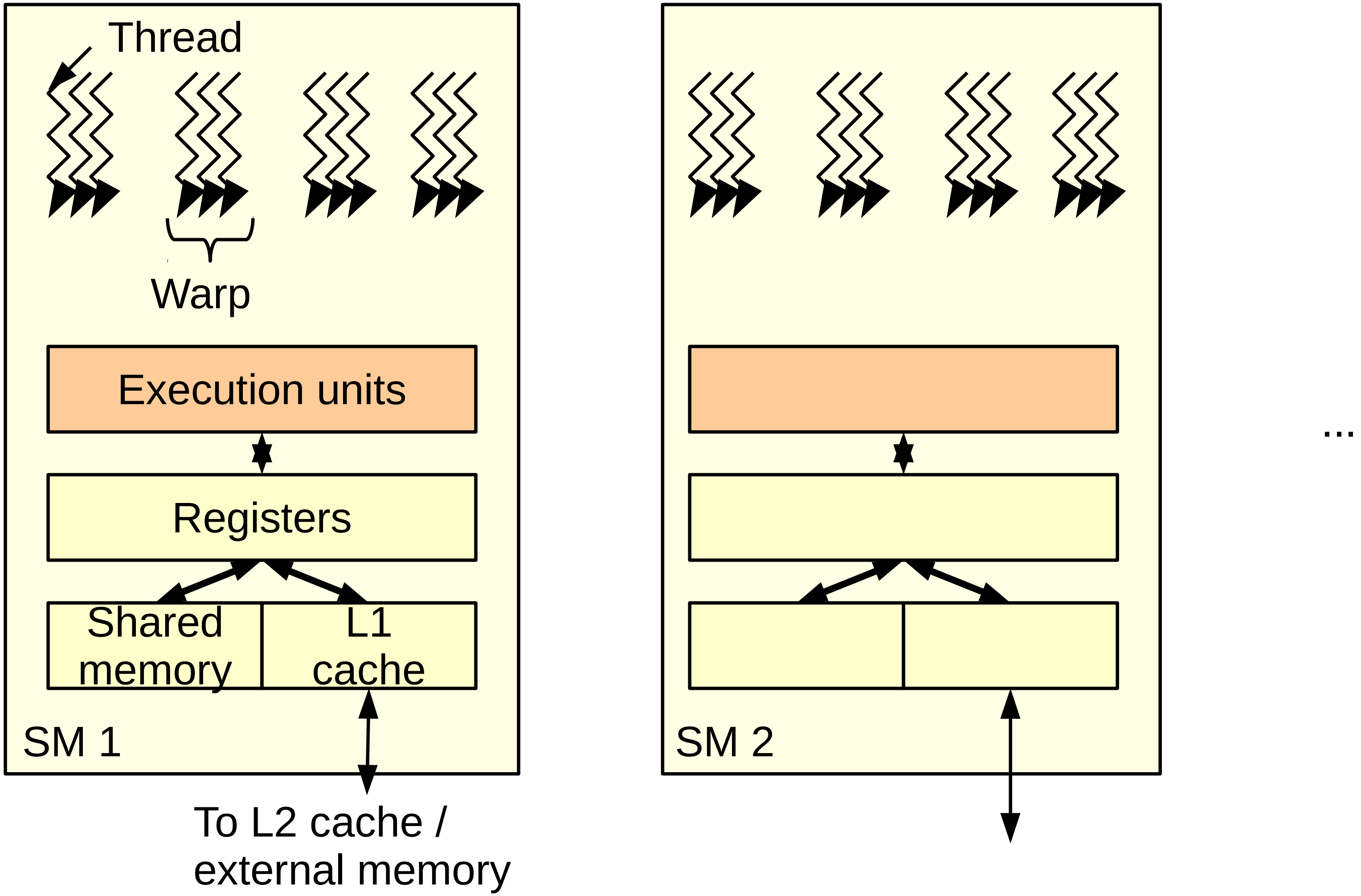
- Processing units
  - Streaming Multiprocessors (SM) in Nvidia jargon
  - Compute Unit (CU) in AMD's
  - Closest equivalent to a CPU core
  - Today: from 1 to 20 SMs in a GPU
- Memory system: caches
  - Keep frequently-accessed data
  - Reduce throughput demand on main memory
  - Managed by hardware (L1, L2) or software (Shared Memory)



GPU processing unit organization

Each SM is a highly-multithreaded processor

- Today: 24 to 48 warps of 32 threads each
  → ~1K threads on each SM, ~10K threads on a GPU



Outline

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  - Technological trends and constraints
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- Forms of parallelism, how to exploit them
  - Why we need (so much) parallelism: latency and throughput
  - Sources of parallelism: ILP, TLP, DLP
  - Uses of parallelism: horizontal, vertical
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  - Putting it all together
  - Architecture of current GPUs: cores, memory
- High-level performance modeling

First-order performance model

Questions you should ask yourself,
before starting to code or optimize

- Will my code run faster on the GPU?
- Is my existing code running as fast as it should?
- Is performance limited by computations or memory bandwidth?

Pen-and-pencil calculations can (often) answer such questions

Performance: metrics and definitions

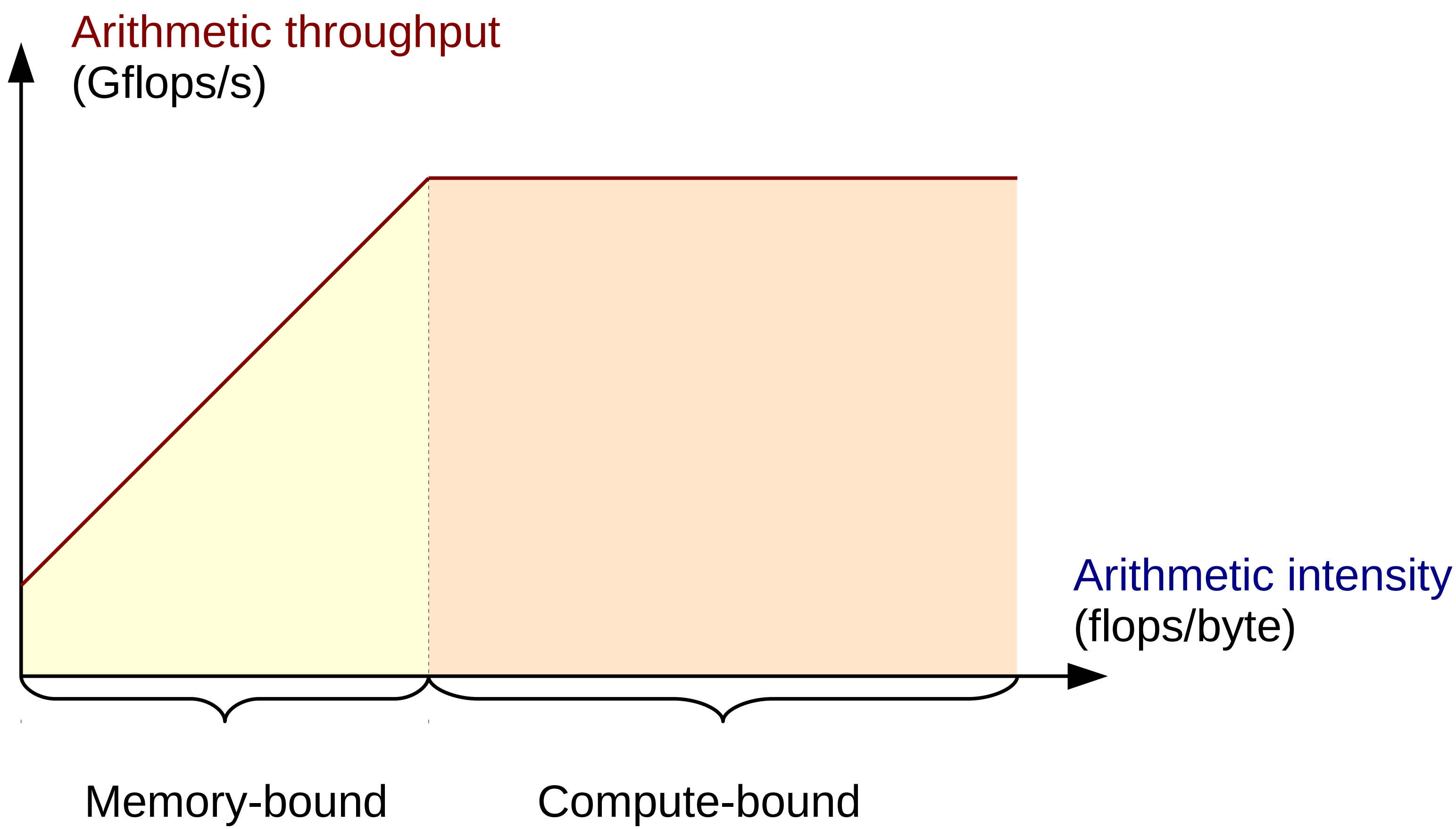
Optimistic evaluation: upper bound on performance

Assume perfect overlap of computations and memory accesses

- Memory accesses: *bytes*
  - Only external memory,
    not caches or registers
- Computations: *flops*
  - Only “useful” computations (usually floating-point)
    not address calculations, loop iterators..
- Arithmetic intensity: *flops / bytes*
  = computations / memory accesses
  - Property of the code
- Arithmetic throughput: *flops / s*
  - Property of code + architecture

The roofline model

- How much performance can I get for a given arithmetic intensity?
  - Upper bound on arithmetic throughput, as a function of arithmetic intensity
  - Property of the architecture



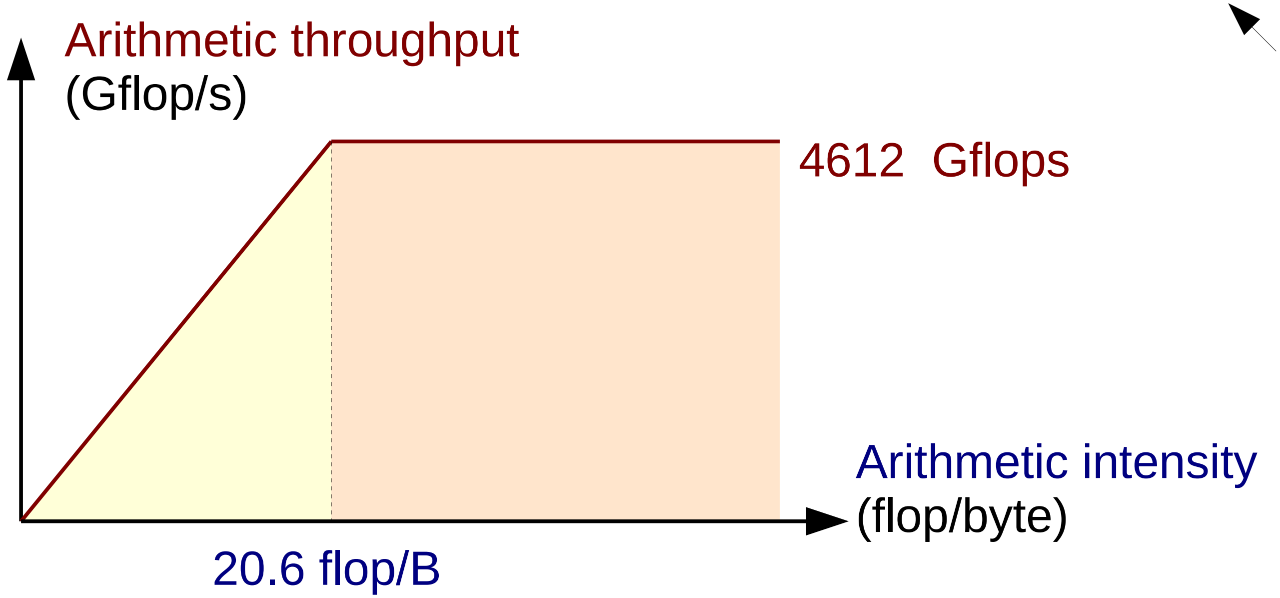
S. Williams, A. Waterman, D. Patterson. *Roofline: an insightful visual performance model for multicore architectures.* Communications of the ACM, 2009

Building the machine model

- Compute or measure:
  - Peak memory throughput *GTX 980*: 224 GB/s
  - Ideal arithmetic intensity = peak compute throughput / mem throughput

GTX 980: 4612 (Gflop/s) / 224 (GB/s) = 20.6 flop/B
× 4 (B/flop) = 82 (dimensionless)

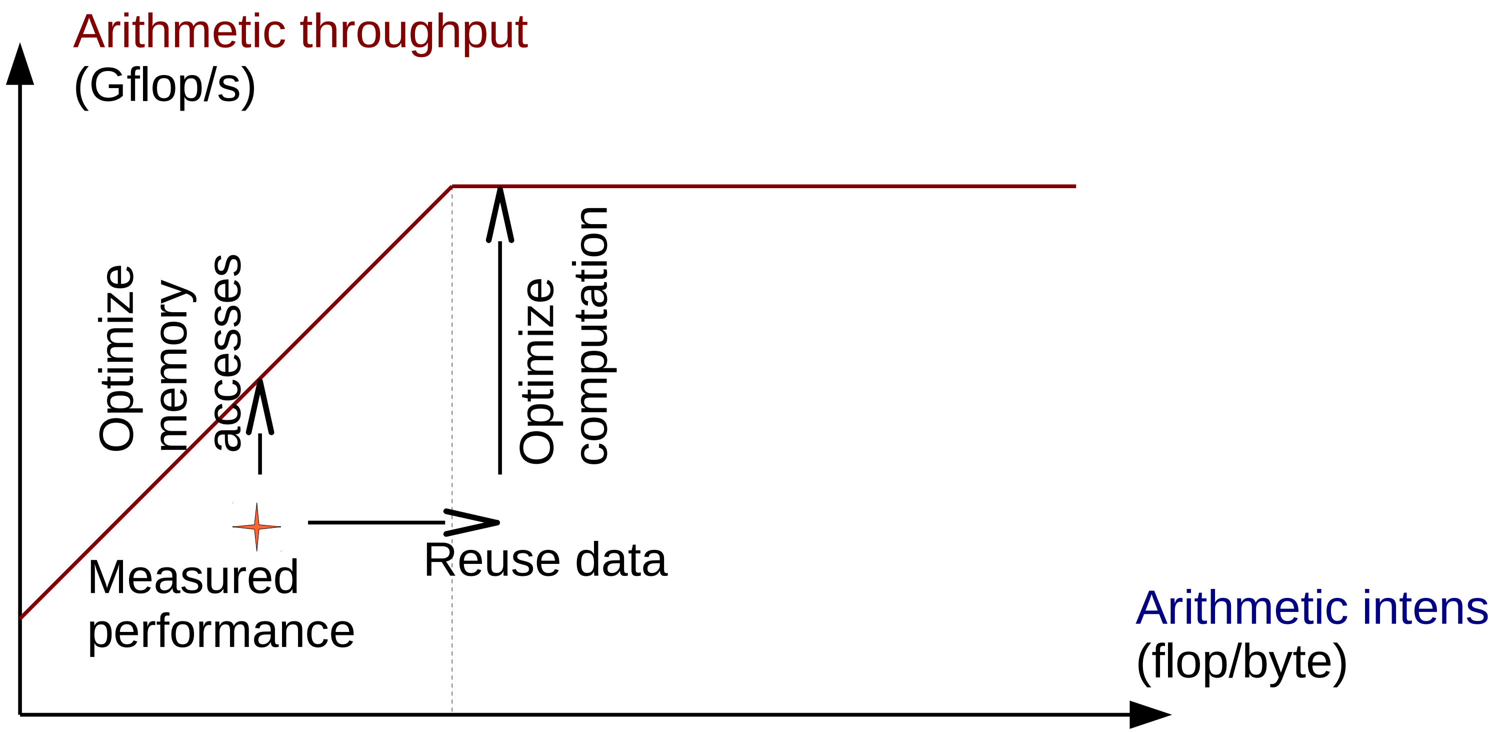
Beware of units:
float=4B, double=8B !



- Achievable peaks may be lower than theoretical peaks
  - Lower curves when adding realistic constraints

Using the model

- Compute arithmetic intensity, measure performance of program
- Identify bottleneck: memory or computation
- Take optimization decision



Example: dot product

```
for i = 1 to n
   r += a[i] * b[i]
```

- How many computations?
- How many memory accesses?
- Arithmetic intensity?
- Compute-bound or memory-bound?
- How many Gflop/s on a GTX 980 GPU?
  - With data in GPU memory?
  - With data in CPU memory?
- How many Gflop/s on an i7 4790 CPU?

GTX 980: 4612 Gflop/s, 224 GB/s
i7 4790: 460 Gflop/s, 25.6 GB/s
PCIe link: 16 GB/s

Example: dot product

```
for i = 1 to n
    r += a[i] * b[i]
```

- How many computations? → 2 n flops
- How many memory accesses? → 2 n words
- Arithmetic intensity? → 1 flop/word = 0.25 flop/B
- Compute-bound or memory-bound? → Highly memory-bound
- How many Gflop/s on a GTX 980 GPU?
  - With data in GPU memory? 224 GB/s × 0.25 flop/B → 56 Gflop/s
  - With data in CPU memory? 16 GB/s × 0.25 flop/B → 4 Gflop/s
- How many Gflop/s on an i7 4790 CPU?

25.6 GB/s × 0.25 flop/B → 6.4 Gflop/s
Conclusion: don't bother porting to GPU!

GTX 980: 4612 Gflop/s, 224 GB/s
i7 4790: 460 Gflop/s, 25.6 GB/s
PCIe link: 16 GB/s

Takeaway

- Result of many tradeoffs
  - Between locality and parallelism
  - Between core complexity and interconnect complexity
- GPU optimized for throughput
  - Exploits primarily DLP, TLP
  - Energy-efficient on parallel applications with regular behavior
- CPU optimized for latency
  - Exploits primarily ILP
  - Can use TLP and DLP when available
- Performance models
  - Back-of-the-envelope calculations and common sense can save time

- Next time: GPU programming in CUDA