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Modern computer architecture

An introduction for software developers

Multi-core today: Intel Xeon Ice Lake (2021)

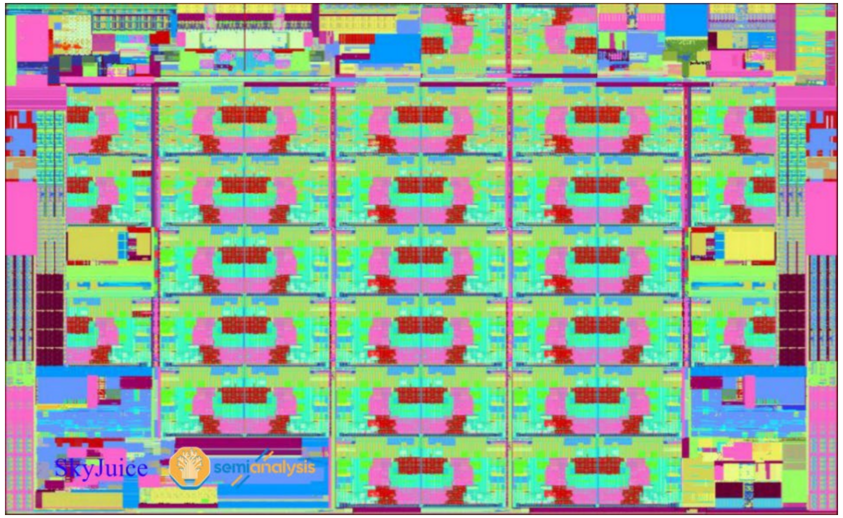
- Xeon “Ice Lake SP” (Platinum/Gold/Silver/Bronze):
  Up to 40 cores running at 2+ GHz (+ “Turbo Mode” 3.7 GHz),

- Simultaneous Multithreading
  → reports as 80-way chip

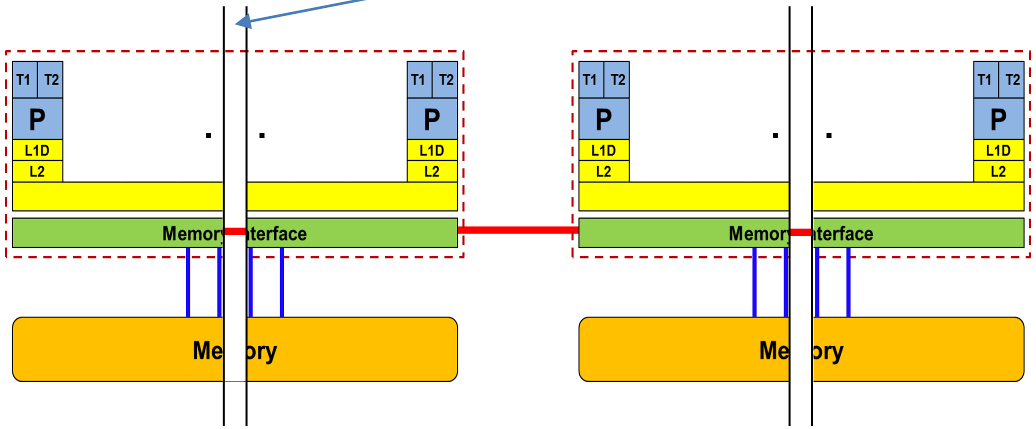
- ~15 Billion Transistors / ~10 nm / up to 270 W

- Die size: up to ~600 mm^2

- Clock frequency:
  flexible ☺



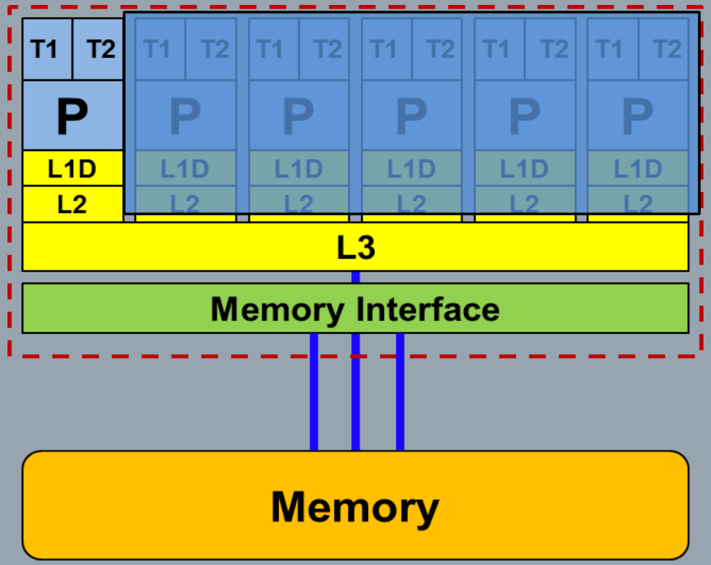
Optional: “Sub-NUMA Clustering” (SNC) mode
(a.k.a.) Cluster-on-Die



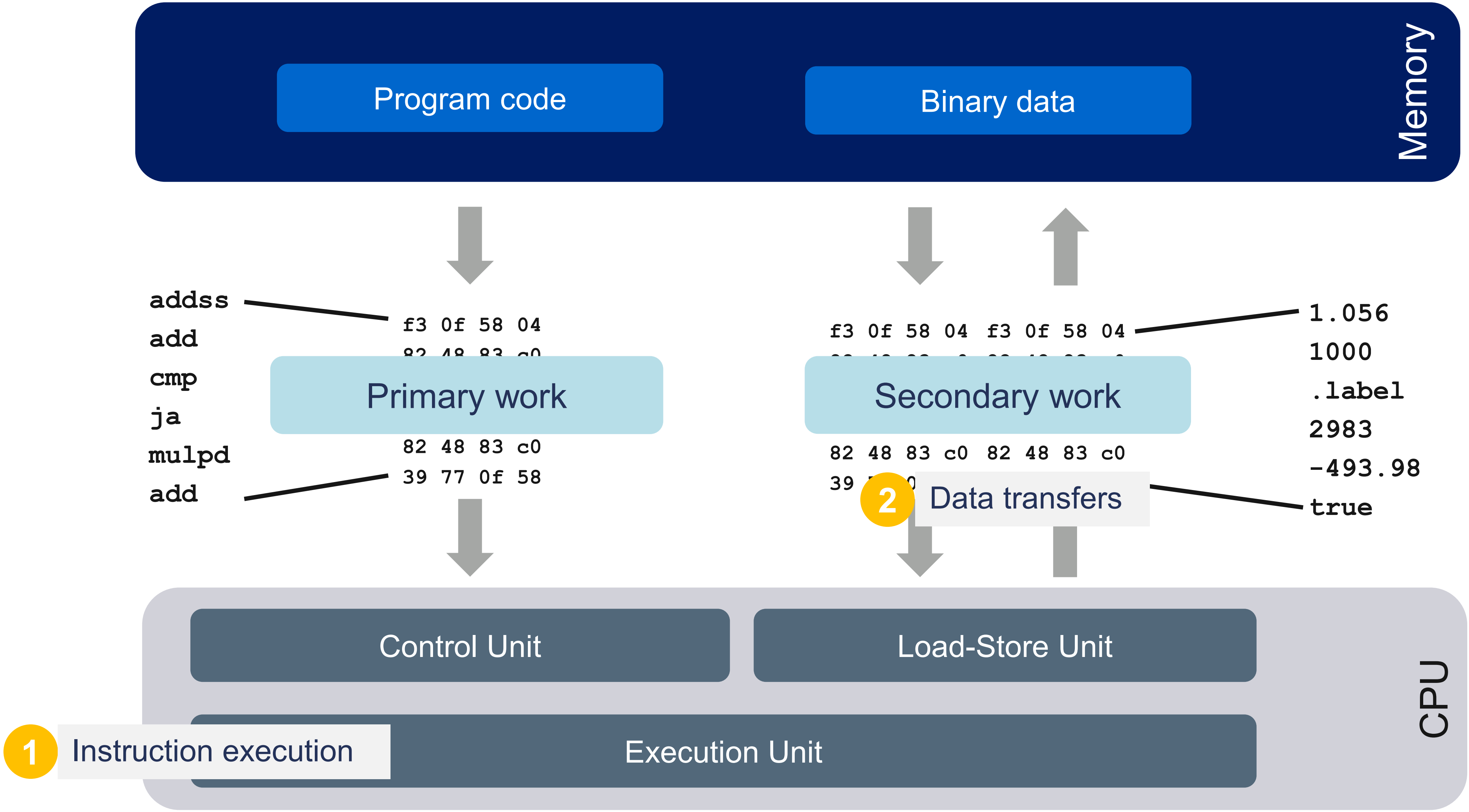
2-socket server

https://ark.intel.com/content/www/us/en/ark.html#@PanelLabel595

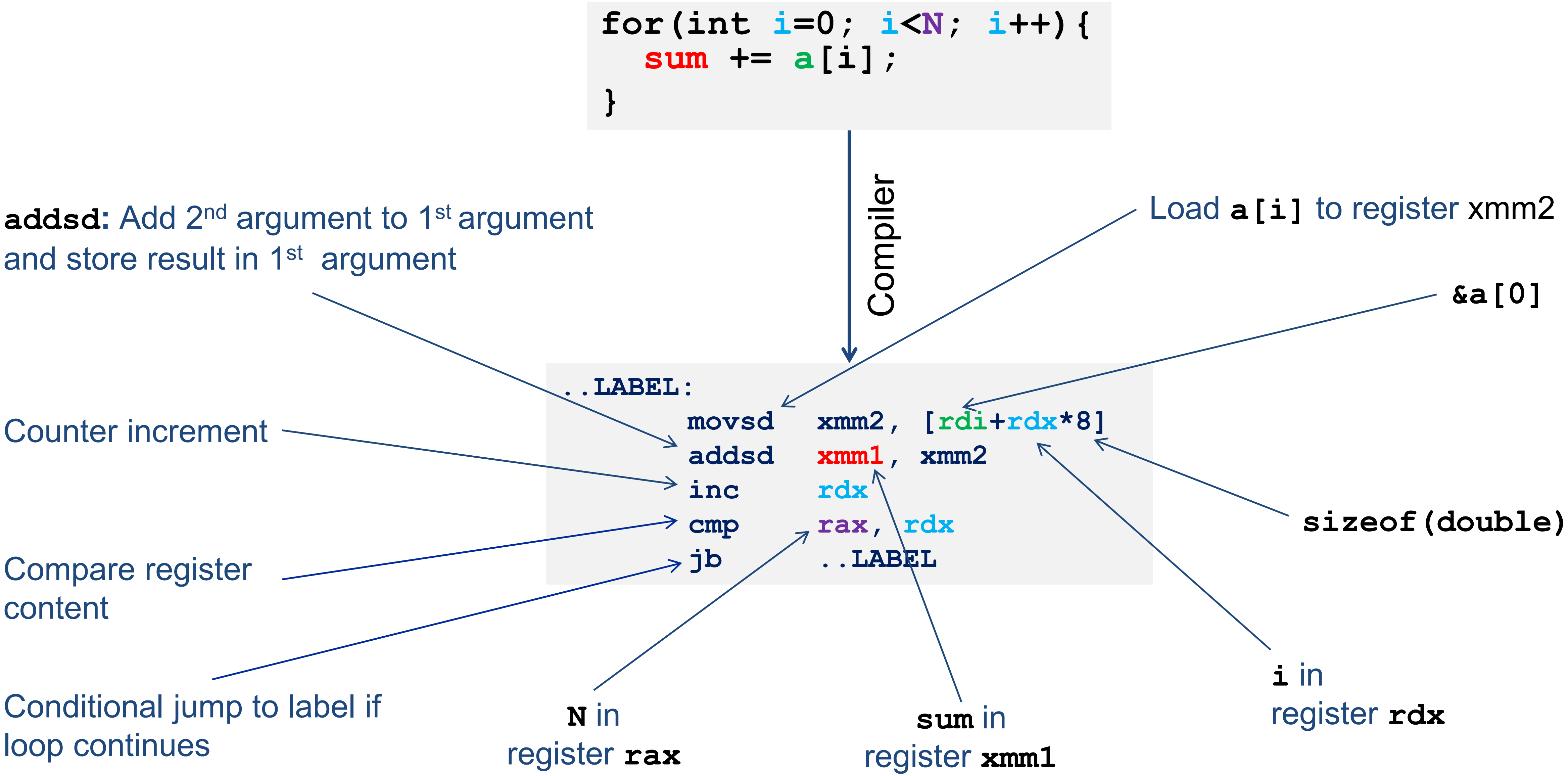
A deeper dive into core architecture



Stored Program Computer



From high level code to actual execution



```
for(int i=0; i<N; i++){
   sum += a[i];
}
```

Compiler

```
..LABEL:
        movsd   xmm2, [rdi+rdx*8]
        addsd   xmm1, xmm2
        inc     rdx
        cmp     rax, rdx
        jb      ..LABEL
```

addsd: Add 2nd argument to 1st argument and store result in 1st argument

Counter increment

Compare register content

Conditional jump to label if loop continues

N in register **rax**

sum in register **xmm1**

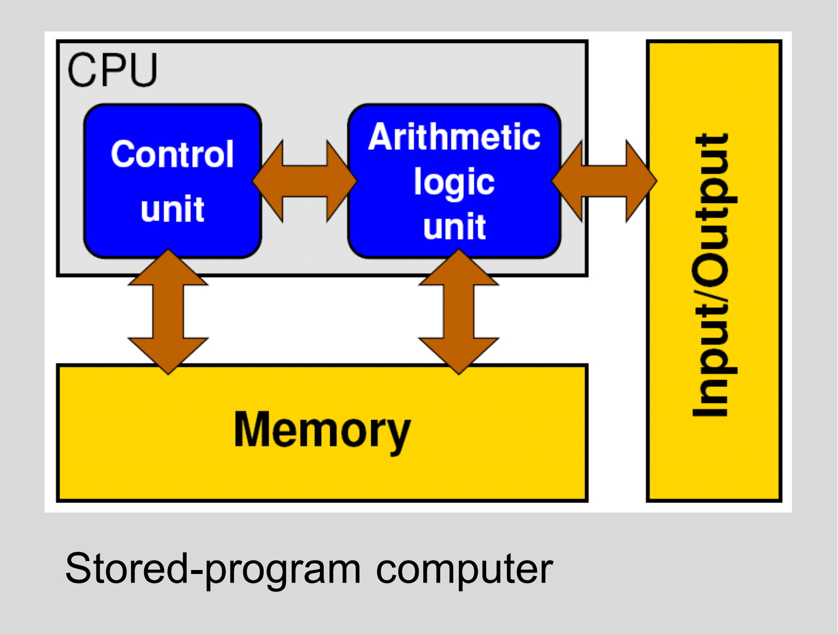
i in register **rdx**

sizeof(double)

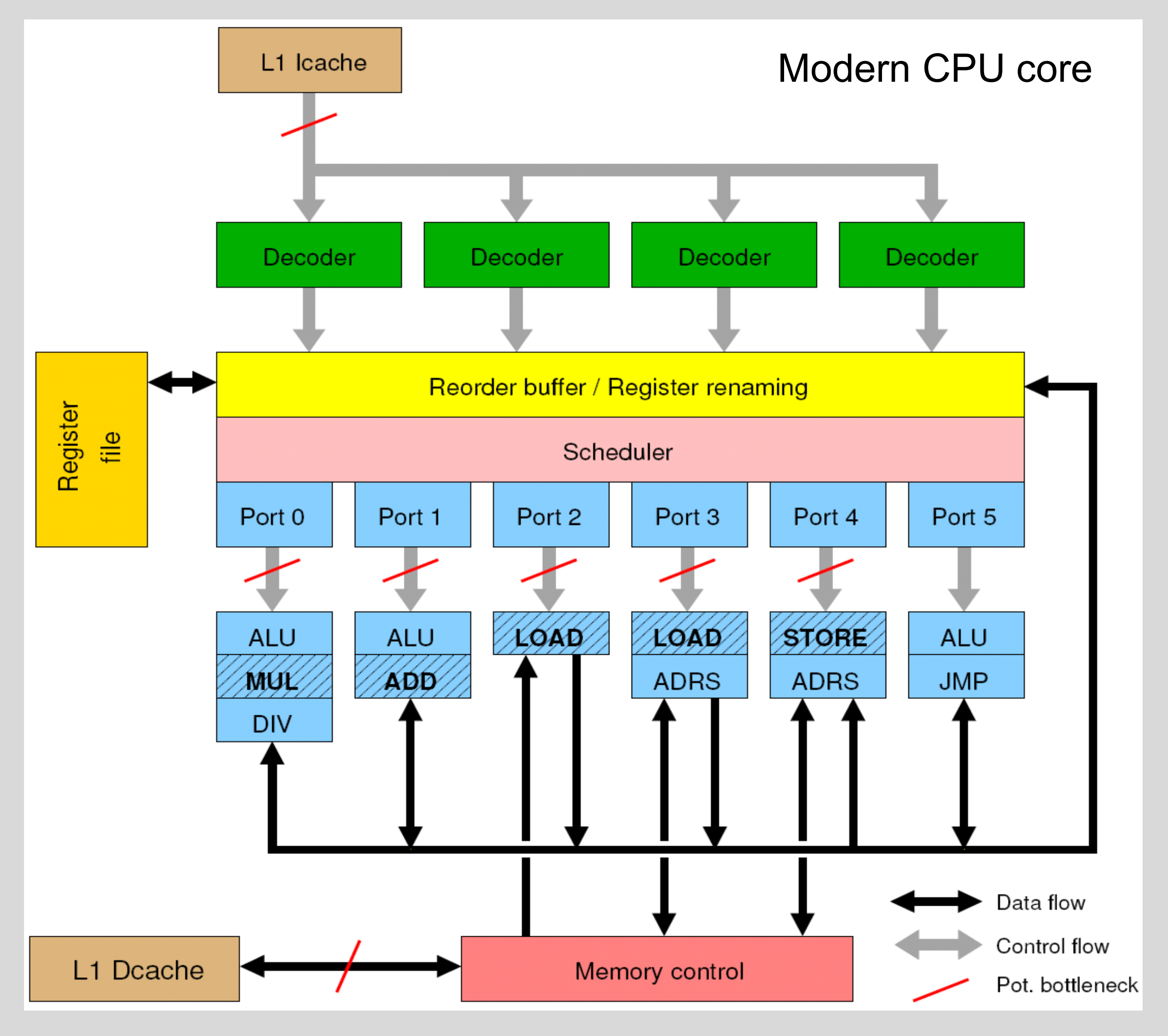
&a[0]

Load **a[i]** to register xmm2

General-purpose cache based microprocessor core



Stored-program computer



- Implements “Stored Program Computer” concept (Turing 1936)
- Similar designs on all modern systems
- (Still) multiple potential bottlenecks

The clock cycle is the “heartbeat” of the core

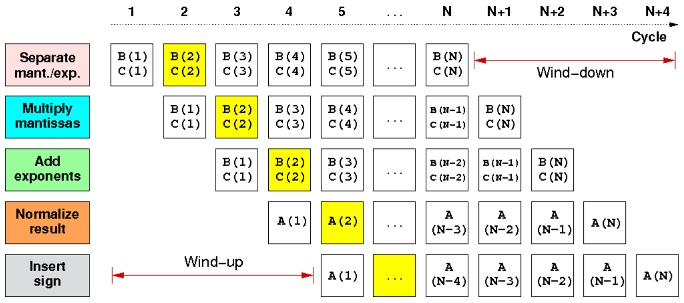
In-core features

Pipelining, Superscalarity, SIMD, SMT

Important in-core features

Pipelining:

Instruction execution in multiple steps



	1	2	3	4	5	...	N	N+1	N+2	N+3	N+4

Separate mant./exp.	B(1)
	C(1)
		B(2)
		C(2)
			B(3)
			C(3)
				B(4)
				C(4)
					B(5)
					C(5)
						...	B(N)
							C(N)
								Wind–down			

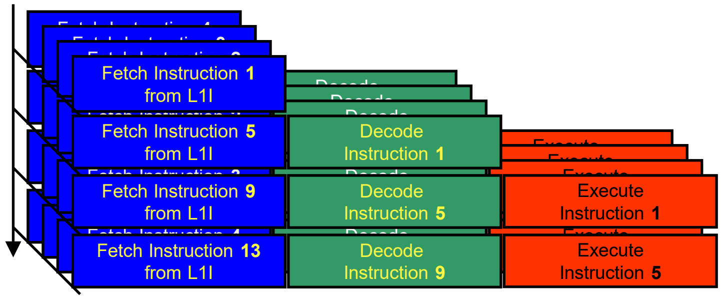
Multiply mantissas		B(1)
		C(1)
			B(2)
			C(2)
				B(3)
				C(3)
					B(4)
					C(4)
						...	B(N−1)
							C(N−1)
								B(N)
								C(N)			

Add exponents			B(1)
			C(1)
				B(2)
				C(2)
					B(3)
					C(3)
						...	B(N−2)
							C(N−2)
								B(N−1)
								C(N−1)
									B(N)
									C(N)		

Normalize result				A(1)	A(2)	...	A(N−3)	A(N−2)	A(N−1)	A(N)	
Insert sign	Wind–up				A(1)	...	A(N−4)	A(N−3)	A(N−2)	A(N−1)	A(N)

Superscalarity:

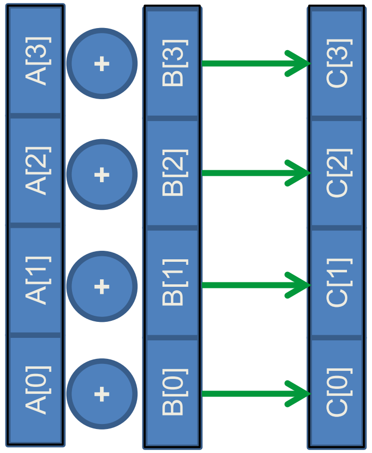
Multiple instructions per cycle



Fetch Instruction 1 from L1I
Fetch Instruction 5 from L1I
Fetch Instruction 9 from L1I
Fetch Instruction 13 from L1I
Decode Instruction 1
Decode Instruction 5
Decode Instruction 9
Execute Instruction 1
Execute Instruction 5

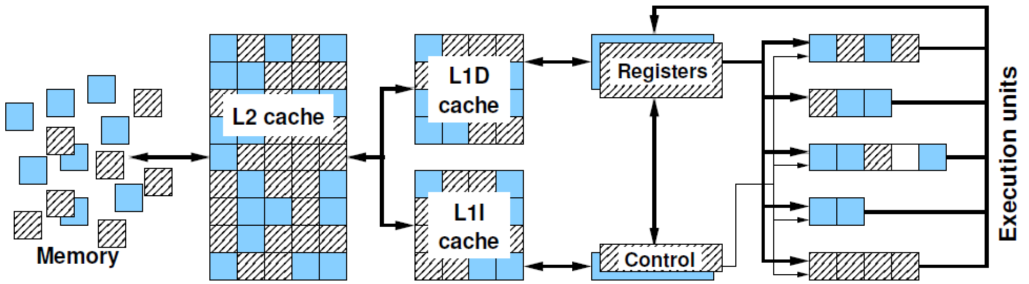
Single Instruction Multiple Data:

Multiple operations per instruction



Simultaneous Multi-Threading:

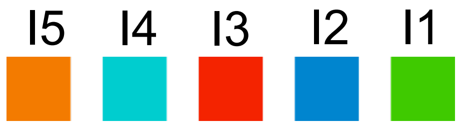
Multiple instruction sequences in parallel



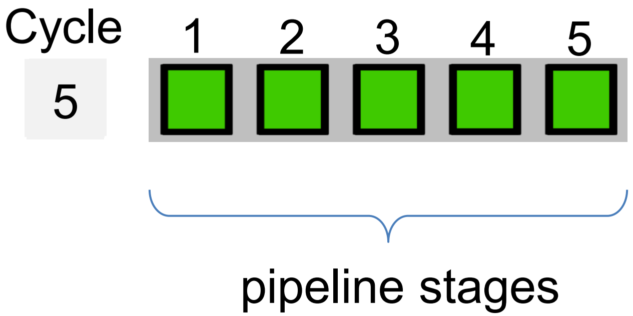
Instruction level parallelism (ILP): pipelining, superscalarity

Pipelining

Independent instructions
(of one kind, e.g., ADD):



Single instruction takes 5 cycles (latency)



Throughput:

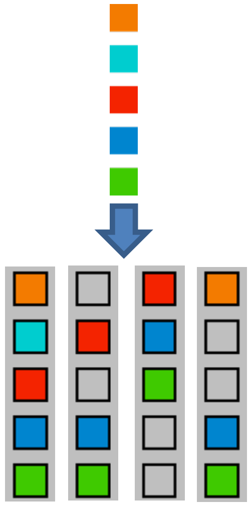
1 instruction per cycle after pipeline is full

→ 5x speedup

Superscalar execution

across multiple pipelines

4-way superscalar:



→ Massive boost in instruction throughput

→ Instructions can be reordered on the fly

Superscalar out-of-order execution and steady state

Instruction execution

STORE
(Latency: 2 cy)

LOAD
(Latency: 4 cy)

ADD
(Latency: 3cy)

```
for(int i=1; i<n; ++i)
        a[i] = a[i] + c;
```

Cycle 1	*load a[1]*		
Cycle 2	*load a[2]*		
Cycle 3	*load a[3]*		
Cycle 4	*load a[4]*		
Cycle 5	*load a[5]*	*add a[1]=c,a[1]*	
Cycle 6	*load a[6]*	*add a[2]=c,a[2]*	
Cycle 7	*load a[7]*	*add a[3]=c,a[3]*	
Cycle 8	*load a[8]*	*add a[4]=c,a[4]*	*store a[1]*
Cycle 9	*load a[9]*	*add a[5]=c,a[5]*	*store a[2]*
Cycle 10	*load a[10]*	*add a[6]=c,a[6]*	*store a[3]*
Cycle 11	*load a[11]*	*add a[7]=c,a[7]*	*store a[4]*
Cycle 12	*load a[12]*	*add a[8]=c,a[8]*	*store a[5]*
Cycle 13	*load a[13]*	*add a[9]=c,a[9]*	*store a[6]*
Cycle 14	*load a[14]*	*add a[10]=c,a[10]*	*store a[7]*
Cycle 15	*load a[15]*	*add a[11]=c,a[11]*	*store a[8]*
Cycle 16	*load a[16]*	*add a[12]=c,a[12]*	*store a[10]*
…	…	…	…

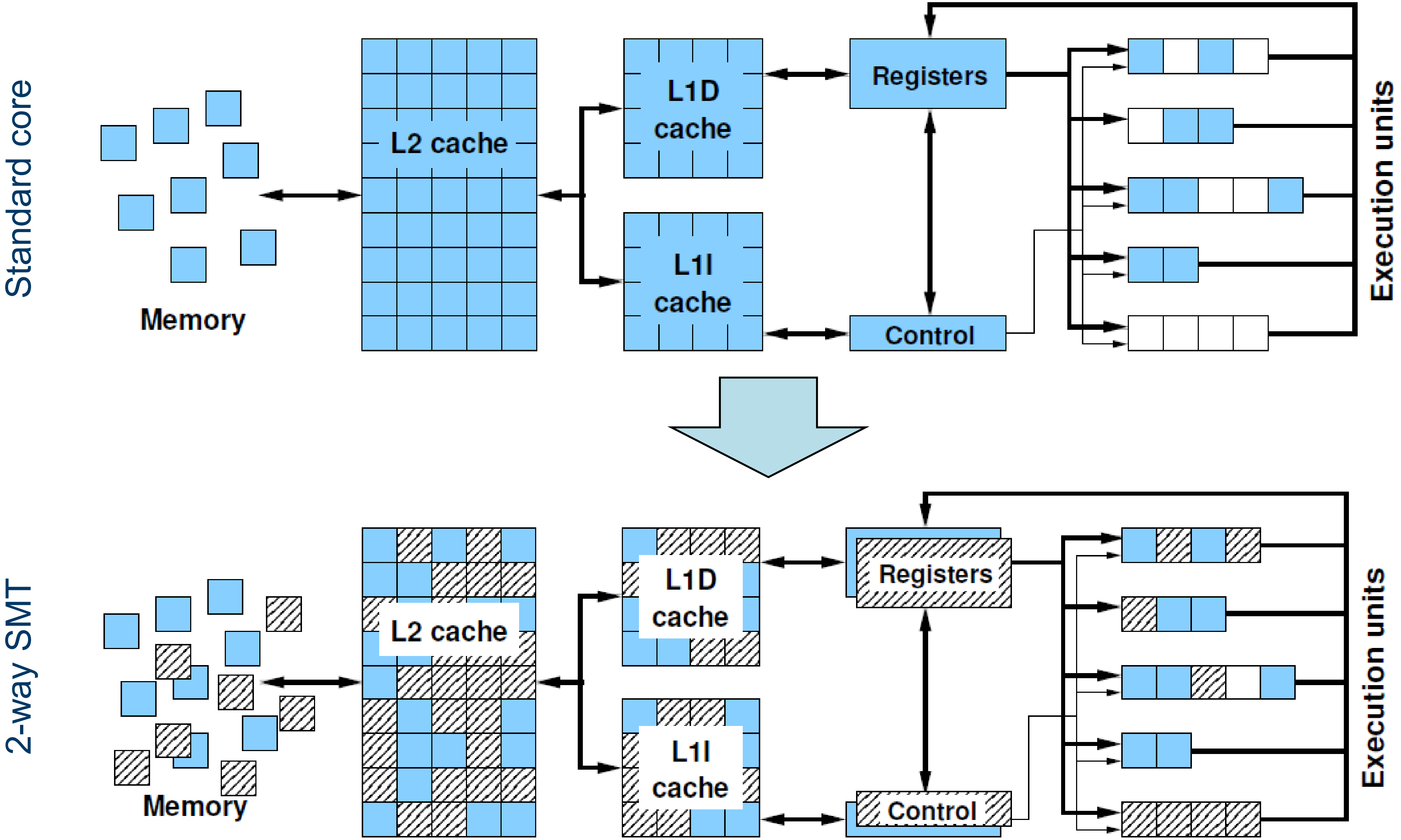
"Steady state:"
3 instructions/cy
("3-way superscalar execution")

Instructions Per Cycle: IPC=3

Cycles Per Instruction: CPI=0.33

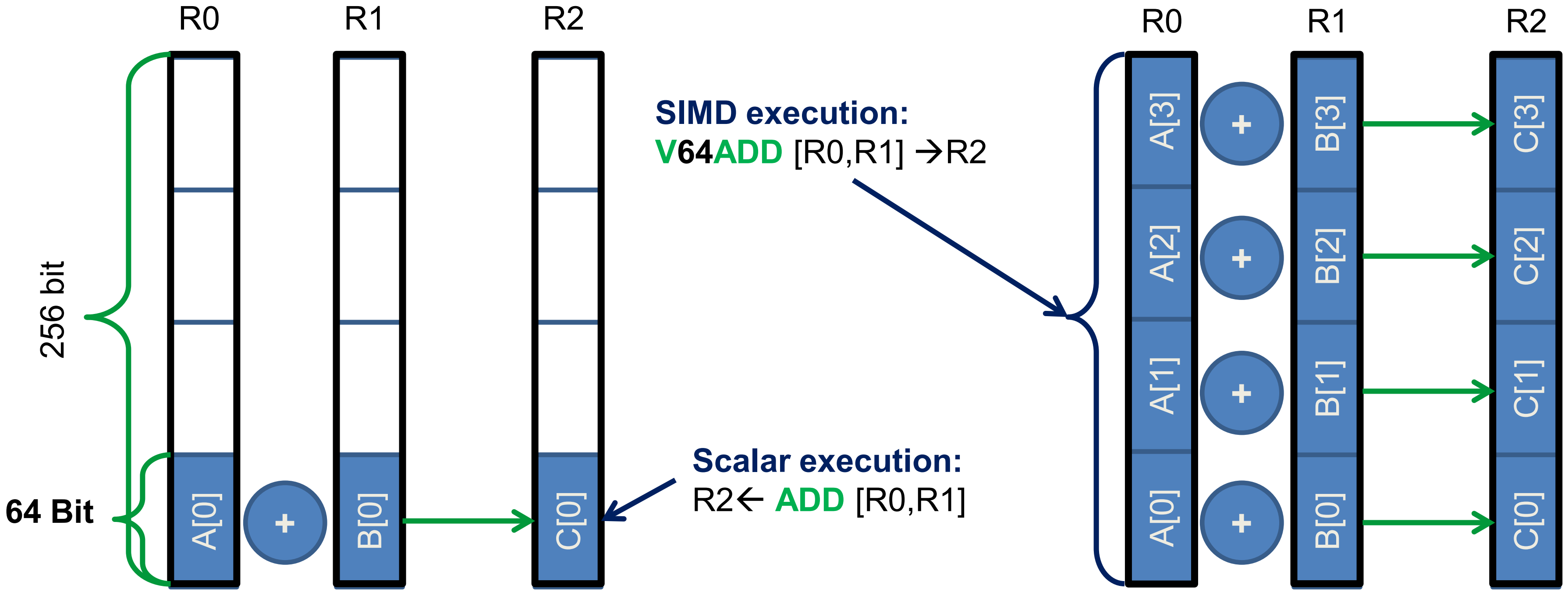
Hardware takes care of executing instructions as soon as their operands are available:
Out-Of-Order (OOO) execution

Simultaneous multi-threading (SMT)



SIMD processing

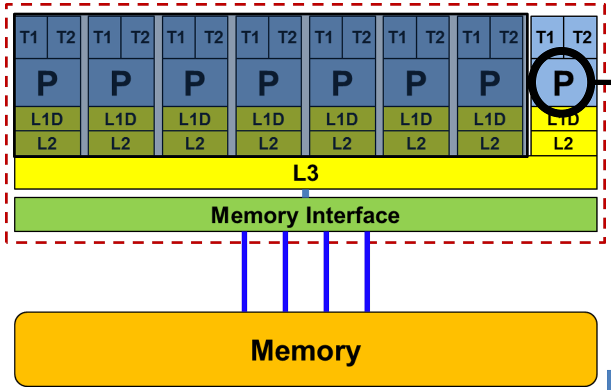
- Single Instruction Multiple Data (SIMD) operations allow the execution of the same operation on “wide” registers from a single instruction
- x86 SIMD instruction sets:
  - SSE: register width = 128 Bit → 2 double precision floating point operands
  - AVX: register width = 256 Bit → 4 double precision floating point operands
  - AVX-512: … you guessed it!
- Adding two registers holding double precision floating point operands:



SIMD execution:
V64ADD [R0,R1] →R2

Scalar execution:
R2← **ADD** [R0,R1]

Single-core DP floating-point performance



$$P_{core} = n_{super}^{FP} \cdot n_{FMA} \cdot n_{SIMD} \cdot f$$

Super-scalarity

FMA factor

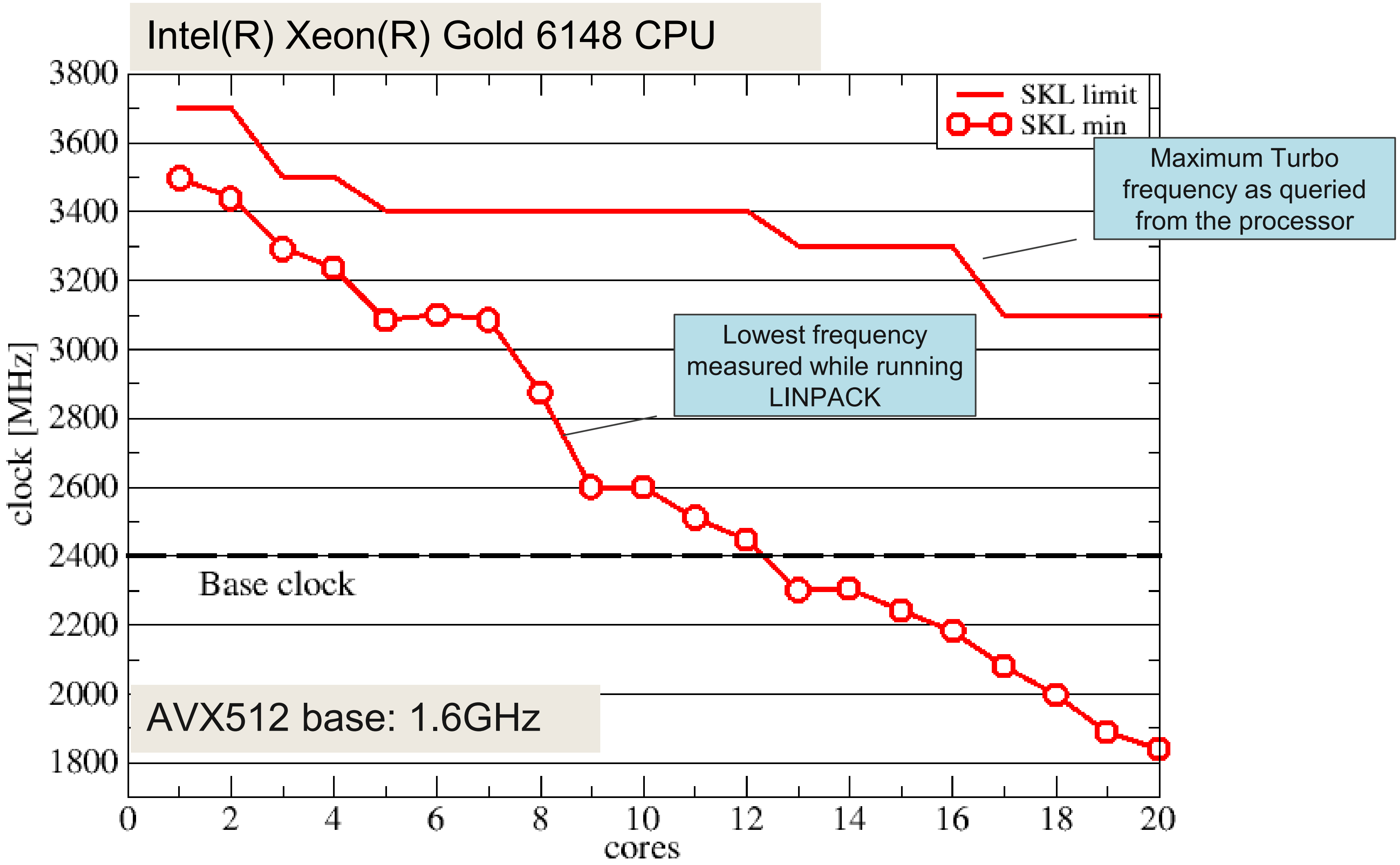
SIMD factor

Clock Speed

Typical representatives	n_{super}^{FP} [inst./cy]	n_{FMA}	n_{SIMD} [ops/inst.]	@market	Ex. model	f [Gcy/s]	P_{core}[GF/s]
Intel Nehalem	2	1	2	Q1/2009	X5570	2.93	11.7
Intel Sandy Bridge	2	1	4	Q1/2012	E5-2680	2.7	21.6
Intel Haswell	2	2	4	Q3/2014	E5-2695 v3	2.3	36.8
Intel Skylake	2	2	8	Q3/2017	Gold 6148	2.4	76.8
Intel Ice Lake	2	2	8	Q2/2021	Platinum 8360Y	2.4	76.8
AMD Zen (Naples)	2	2	2	Q1/2017	Epyc 7451	2.3	18.4
AMD Zen2 (Rome)	2	2	4	Q4/2019	Epyc 7642	2.3	36.8
AMD Zen3 (Milan)	2	2	4	Q4/2020	Epyc 7713	2.0	32.0
Fujitsu A64FX	2	2	8	Q2/2020	FX700	1.8	57.6

Multi-core today: Turbo mode

The processor **dynamically** overclocks to exploit more of the **TDP** envelope if fewer cores are active


Intel(R) Xeon(R) Gold 6148 CPU

Maximum Turbo frequency as queried from the processor

Lowest frequency measured while running LINPACK

AVX512 base: 1.6GHz

Example: The sum reduction

A “simple” example: The sum reduction

```
for (int i=0; i<N; i++){
    sum += a[i];
}
```

…In single precision on an AVX-capable core (ADD latency = 3 cy)

How fast can this loop possibly run with data in the L1 cache?

- Loop-carried dependency on summation variable
- Execution stalls at every ADD until previous ADD is complete

→No pipelining?

→No SIMD?

Applicable peak for the sum reduction (I)

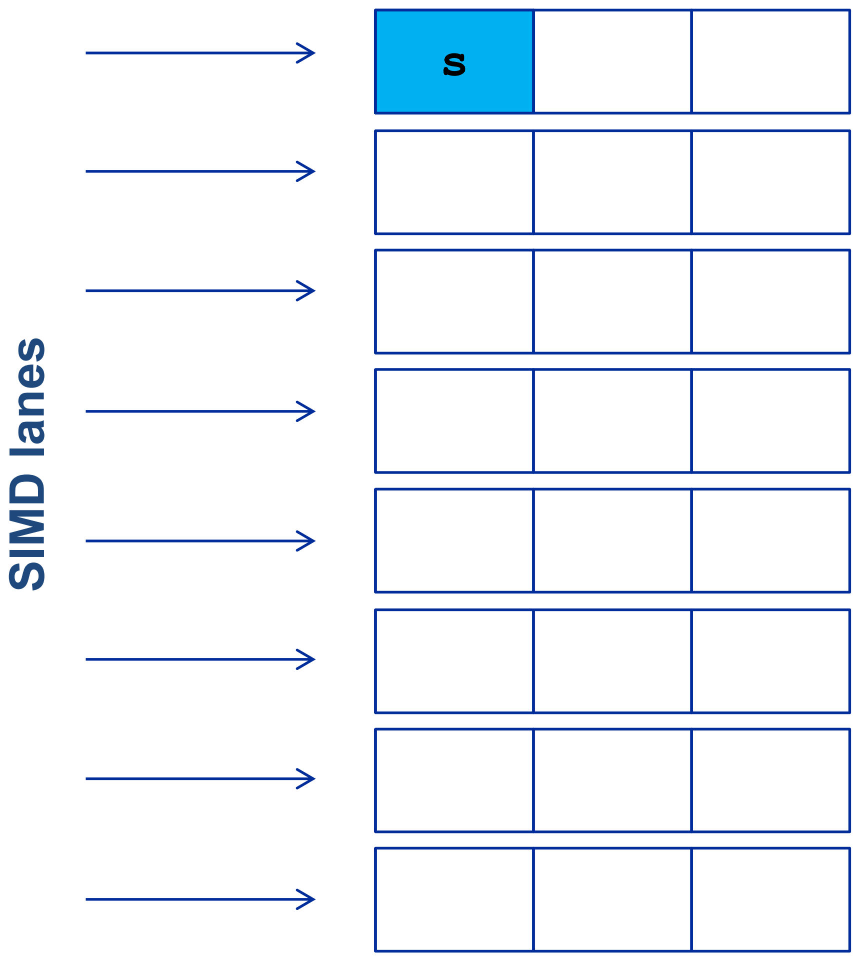
Plain scalar code, no SIMD

```
for (int i=0; i<N; i++){
    sum += a[i];
}
```

SIMD lane

```
LOAD r1.0 ← 0
i ← 1
loop:
  LOAD r2.0 ← a(i)
  ADD r1.0 ← r1.0 + r2.0
  ++i →? loop
result ← r1.0
```

ADD pipes utilization:



→ 1/24 of ADD peak

Applicable peak for the sum reduction (II)

Scalar code, 3-way “modulo variable expansion”

```
LOAD r1.0 ← 0
LOAD r2.0 ← 0
LOAD r3.0 ← 0
i ← 1

loop:
  LOAD r4.0 ← a(i)
  LOAD r5.0 ← a(i+1)
  LOAD r6.0 ← a(i+2)

  ADD r1.0 ← r1.0 + r4.0  # scalar ADD
  ADD r2.0 ← r2.0 + r5.0  # scalar ADD
  ADD r3.0 ← r3.0 + r6.0  # scalar ADD

  i+=3 →? loop
result ← r1.0+r2.0+r3.0
```

```
for (int i=0; i<N; i+=3){
    s1 += a[i+0];
    s2 += a[i+1];
    s3 += a[i+2];
}
sum = sum + s1+s2+s3;
```

s1	s2	s3

→ **1/8 of ADD peak**

Applicable peak for the sum reduction (III)

SIMD vectorization (8-way MVE) x
pipelining (3-way MVE)

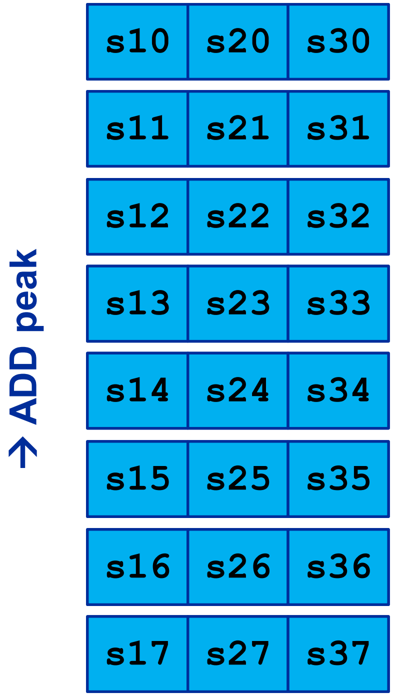
```
LOAD [r1.0,…,r1.7] ← [0,…,0]
LOAD [r2.0,…,r2.7] ← [0,…,0]
LOAD [r3.0,…,r3.7] ← [0,…,0]
i ← 1

loop:
  LOAD [r4.0,…,r4.7] ← [a(i),…,a(i+7)]      # SIMD LOAD
  LOAD [r5.0,…,r5.7] ← [a(i+8),…,a(i+15)]   # SIMD
  LOAD [r6.0,…,r6.7] ← [a(i+16),…,a(i+23)] # SIMD

  ADD r1 ← r1 + r4   # SIMD ADD
  ADD r2 ← r2 + r5   # SIMD ADD
  ADD r3 ← r3 + r6   # SIMD ADD

  i+=24 →? loop
result ← r1.0+r1.1+...+r3.6+r3.7
```

```
for (int i=0; i<N; i+=24){
  s10 += a[i+0]; s20 += a[i+8];  s30 += a[i+16];
  s11 += a[i+1]; s21 += a[i+9];  s31 += a[i+17];
  s12 += a[i+2]; s22 += a[i+10]; s32 += a[i+18];
  s13 += a[i+3]; s23 += a[i+11]; s33 += a[i+19];
  s14 += a[i+4]; s24 += a[i+12]; s34 += a[i+20];
  s15 += a[i+5]; s25 += a[i+13]; s35 += a[i+21];
  s16 += a[i+6]; s26 += a[i+14]; s36 += a[i+22];
  s17 += a[i+7]; s27 += a[i+15]; s37 += a[i+23];
}
sum = sum + s10+s11+…+s37;
```



s10	s20	s30
s11	s21	s31
s12	s22	s32
s13	s23	s33
s14	s24	s34
s15	s25	s35
s16	s26	s36
s17	s27	s37

Sum reduction

Questions

- When can this performance actually be achieved?
  - No data transfer bottlenecks
  - No other in-core bottlenecks
    - Need to execute (3 LOADs + 3 ADDs + 1 increment + 1 compare + 1 branch) in 3 cycles

- What does the compiler do?
  - If allowed and capable, the compiler will do this automatically

- Is the compiler allowed to do this at all?
  - Not according to language standards
  - High optimization levels can violate language standards

- What about the “accuracy” of the result?
  - Good question ;-)

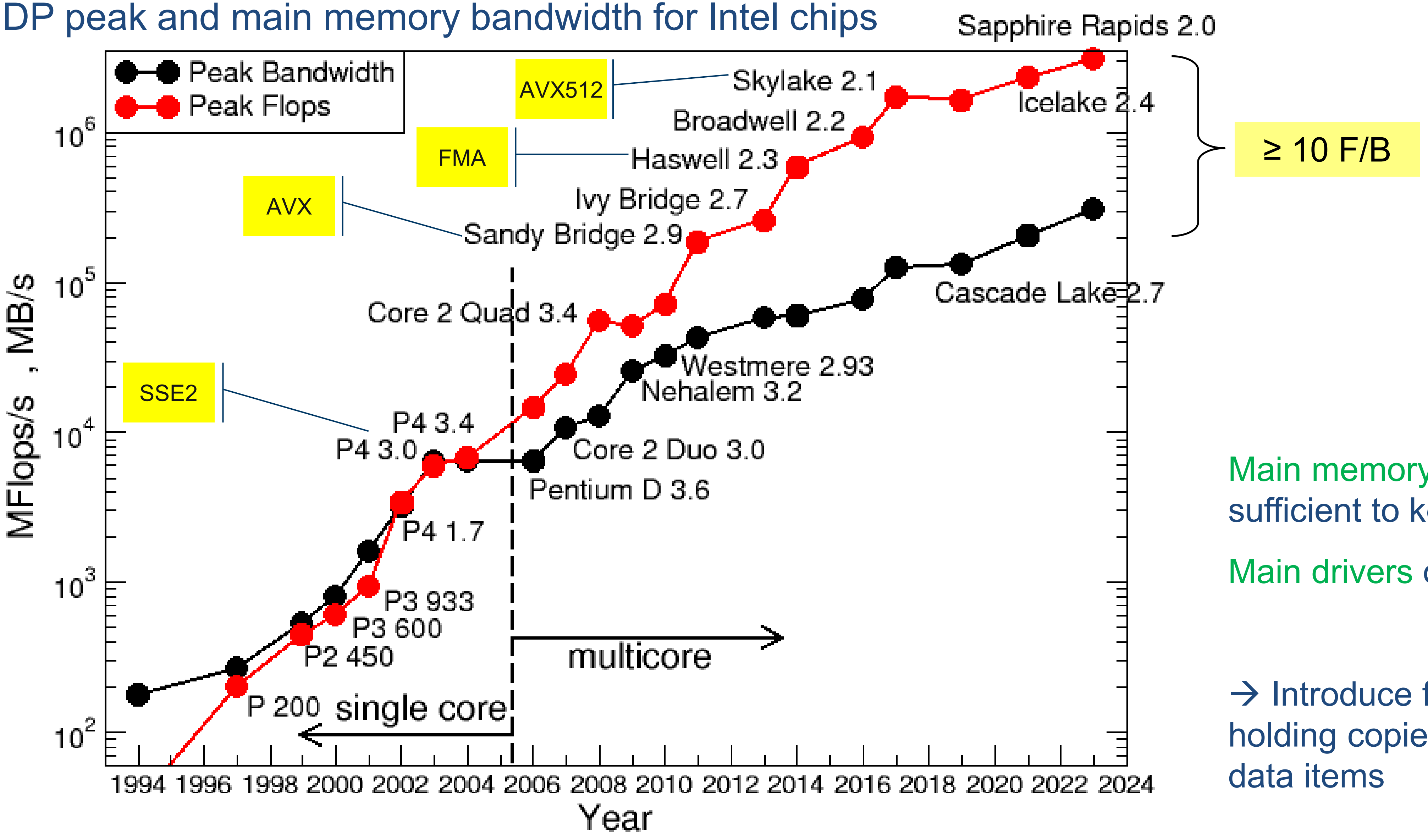
Memory Hierarchy

In-cache performance (L2, L3)

Main memory performance

Von Neumann bottleneck reloaded: “DRAM gap”

DP peak and main memory bandwidth for Intel chips

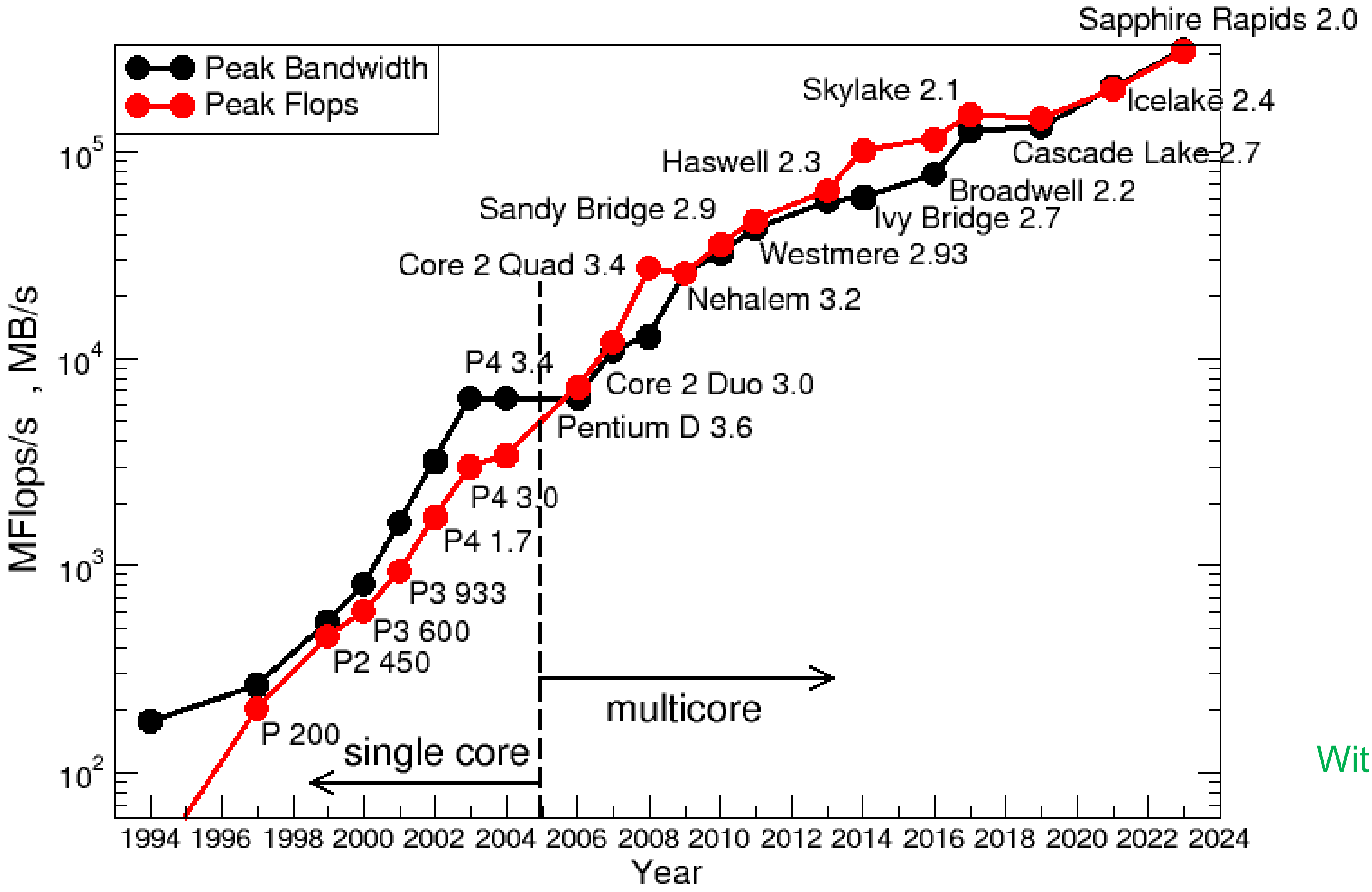


Main memory access speed not sufficient to keep CPU busy…

Main drivers of gap: SIMD, FMA

→ Introduce fast on-chip caches, holding copies of recently used data items

The “stripped” von Neumann bottleneck



Without SIMD, FMA: no gap!

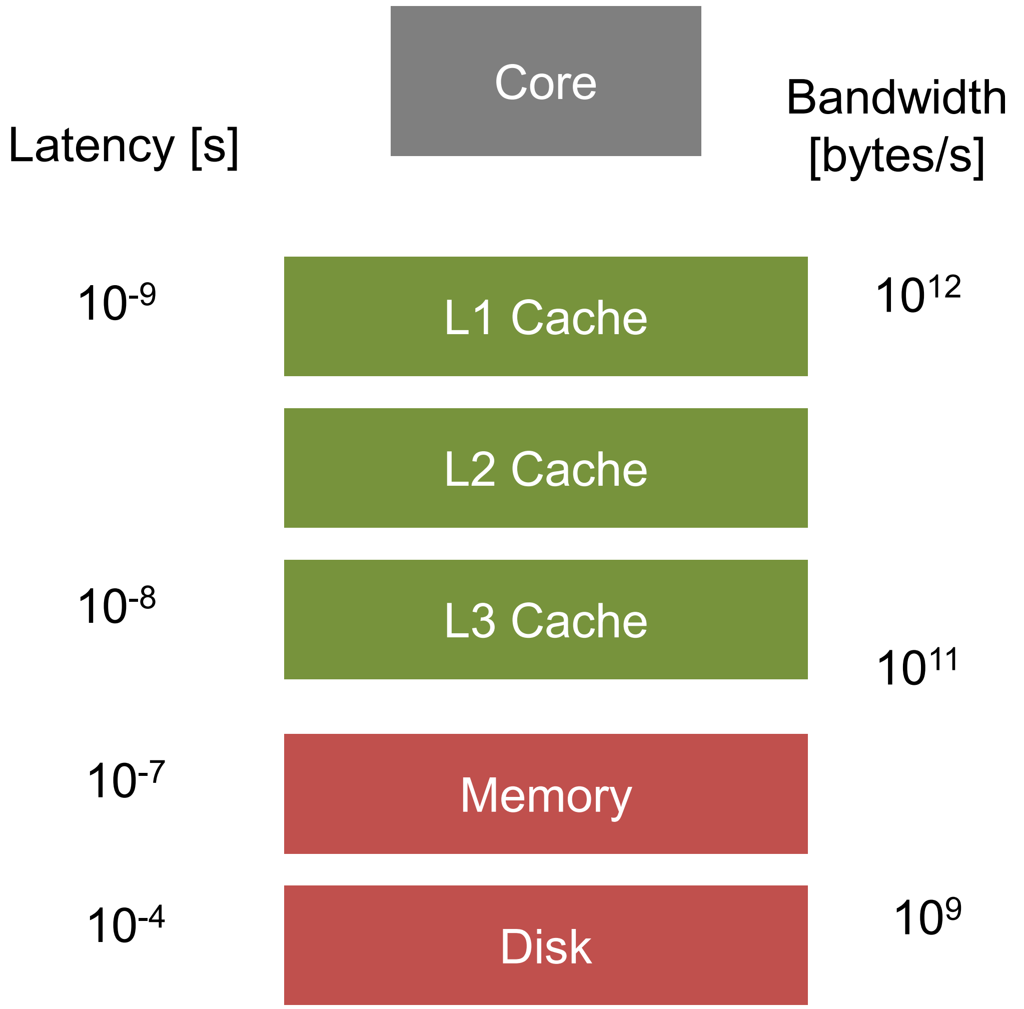
Memory hierarchy

You can either build a

small and fast memory

or a

large and slow memory

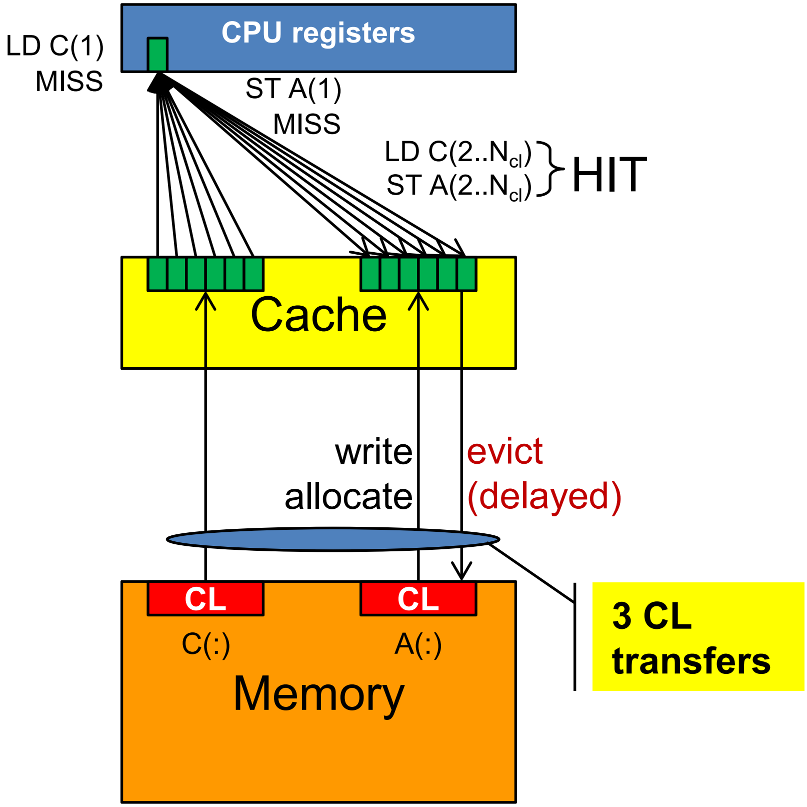


Purpose of many optimizations: use data in fast memory

Data transfers in a memory hierarchy

Caches help with getting instructions and data to the CPU "fast"

How does data travel from memory to the CPU and back?



- Remember: Caches are organized in cache lines (e.g., 64 bytes)
- Only complete cache lines are transferred between memory hierarchy levels (except registers)
- Registers can only "talk" to the L1 cache
- MISS: Load or store instruction does not find the data in acache level
  → CL transfer required

- Example: Array copy `A(:)=C(:)`

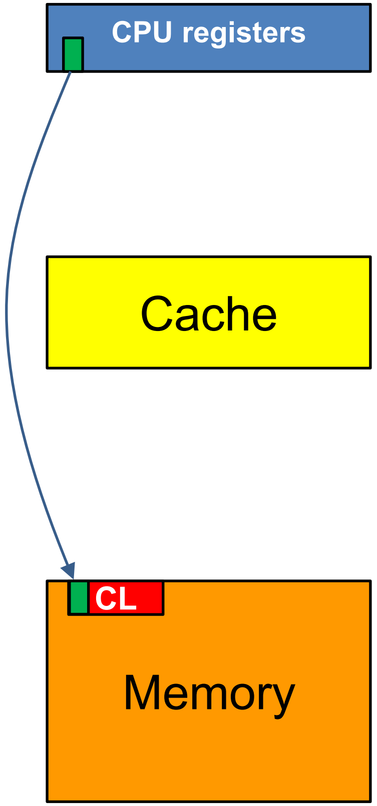
Avoiding the write-allocate transfer

Disadvantages of write-allocate:

- Cache pollution (if data not needed anytime soon)
- Additional data traffic

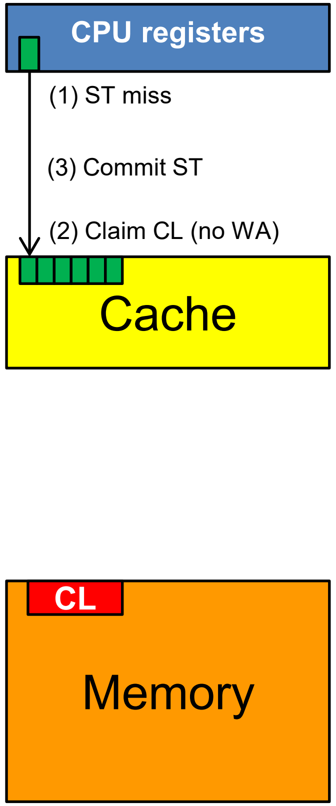
Solution 1:
Nontemporal stores

- A.k.a. “streaming stores,” store instruction with a “nontemporal hint”
- Write “directly” to memory, ignoring the normal cache hierarchy
- Avoids cache pollution, but stored data ends up in memory

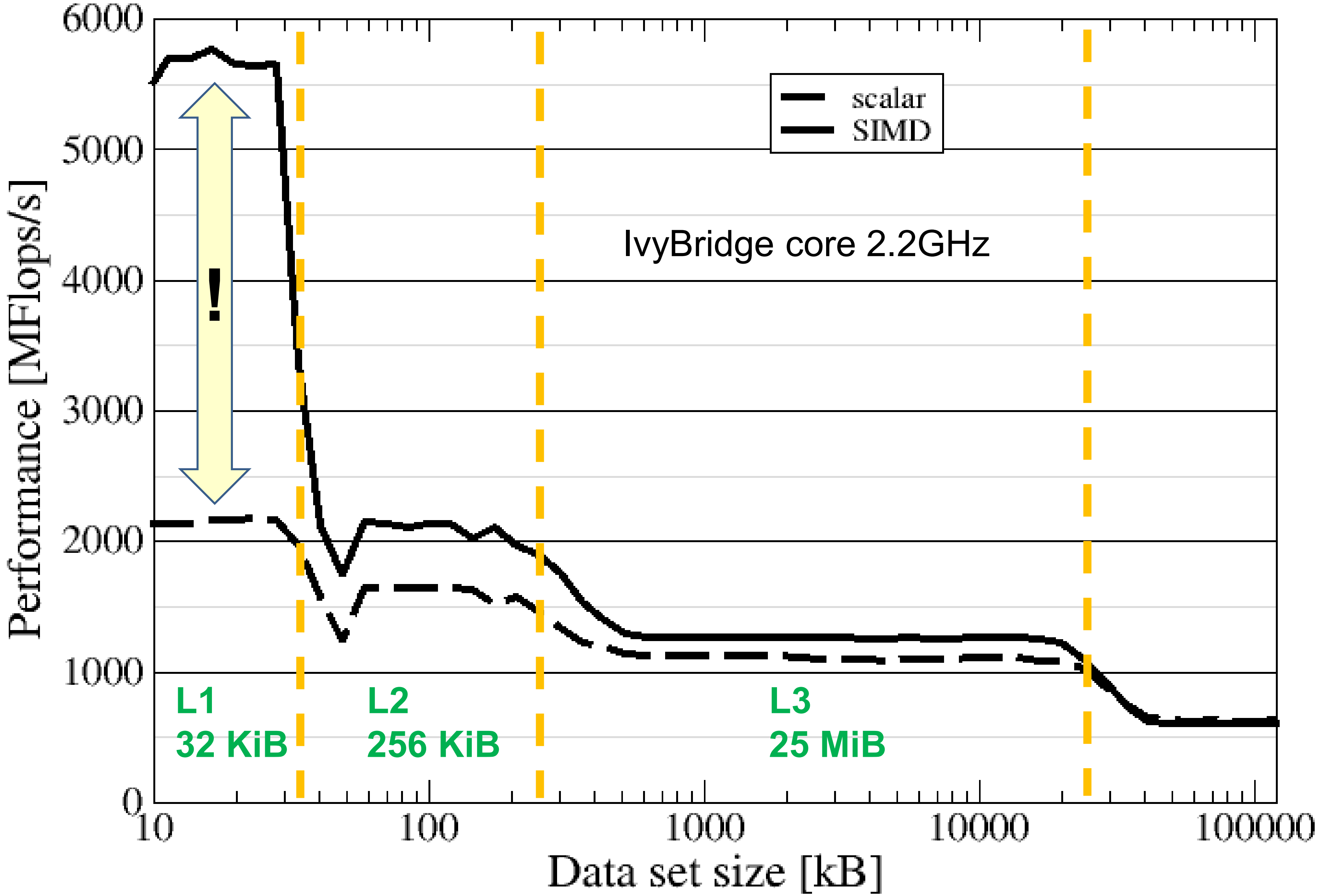


Solution 2:
Cache line claim

- Special instructions (e.g., on POWER, A64FX) or automatic in hardware (Arm, Intel Ice Lake)
- Core claims CL in some level when guranteed to be overwritten completely
- Allows stored data to remain in cache → does not reduce cache pollution



Getting the data from far away



```
A(:) = B(:) + C(:) * D(:)
```

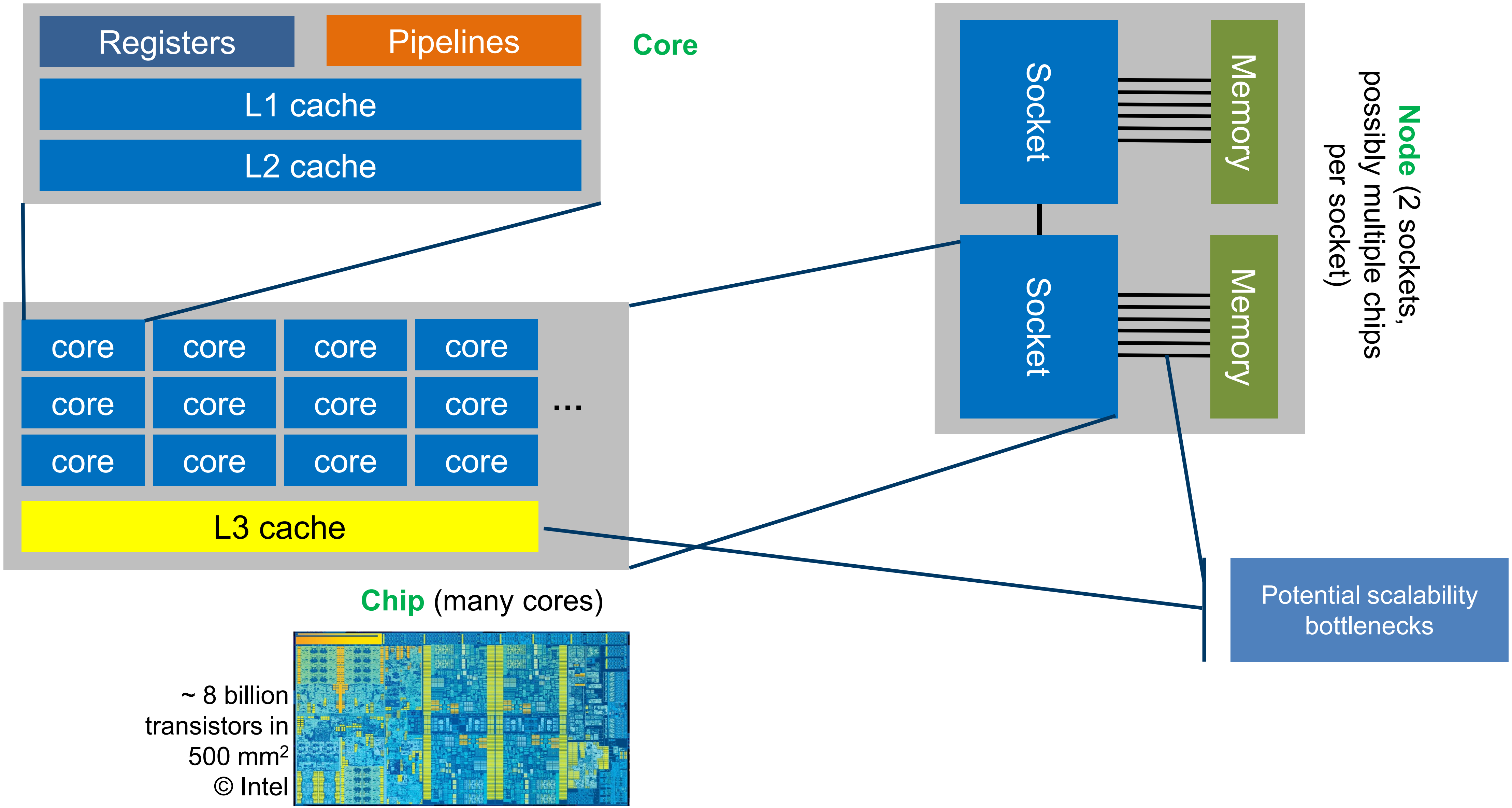
Varying loop length, repeat many times

Multicore Chips

Memory bandwidth scaling

Node topology and performance

Node topology of HPC systems



Registers

Pipelines

L1 cache

L2 cache

Core

core core core core

core core core core …

core core core core

L3 cache

Chip (many cores)

~ 8 billion transistors in 500 mm^2 © Intel

Socket

Memory

Socket

Memory

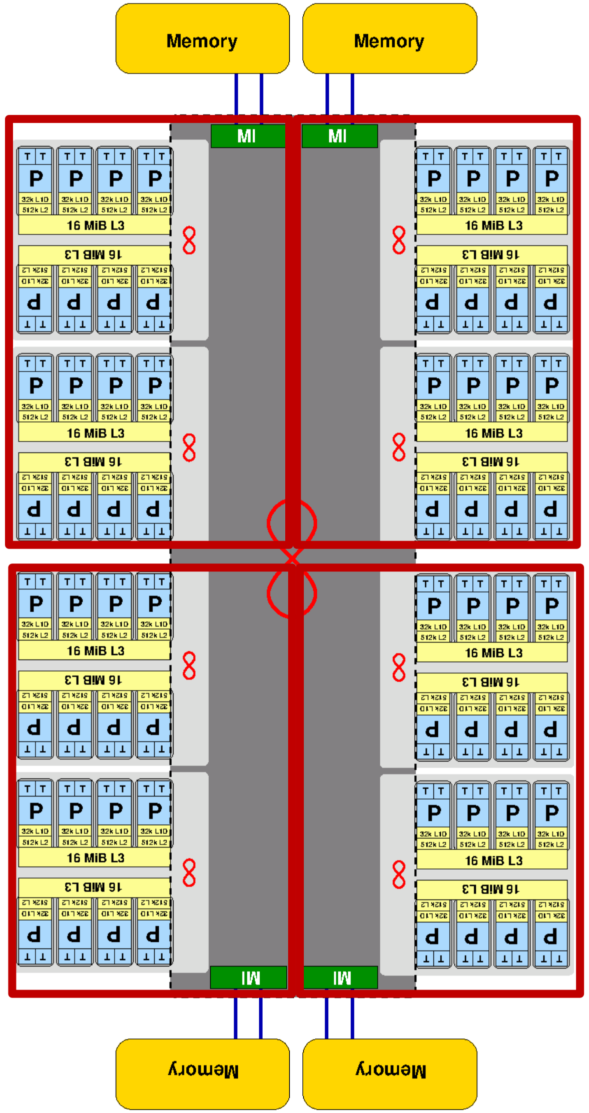
Node (2 sockets, possibly multiple chips per socket)

Potential scalability bottlenecks

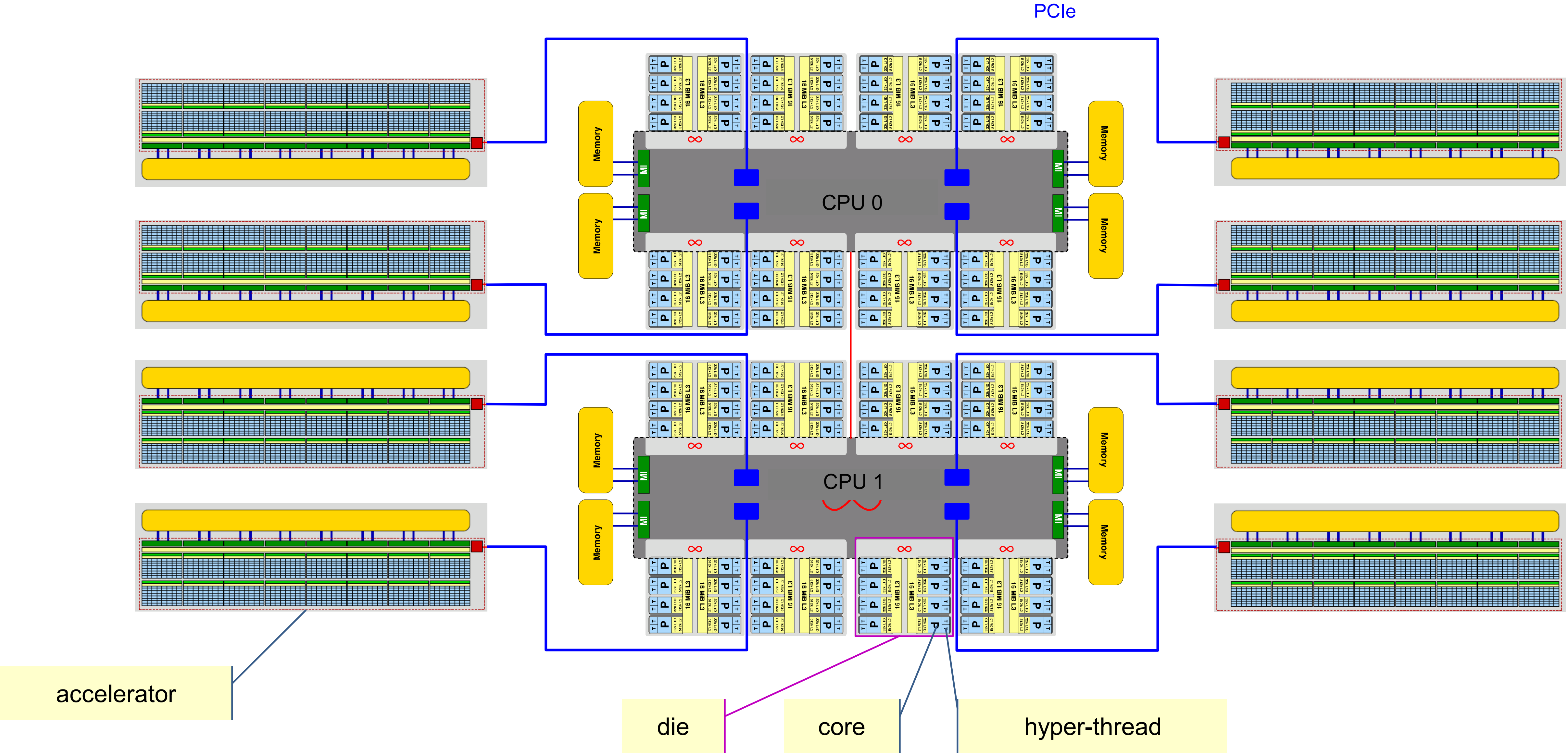
Putting the cores & caches together
AMD Epyc 7742 64-Core Processor («Rome»)

- Core features:
  - Two-way SMT
  - Two 256-bit SIMD FMA units (AVX2) →16 flops/cycle
  - 32 KiB L1 data cache per core
  - 512 KiB L2 cache per core
- 64 cores per socket hierarchically built up from
  - 16 CCX with 4 cores and 16 MiB of L3 cache
  - 2 CCX form 1 CCD (silicon die)
  - 8 CCDs connected to IO device “Infinity Fabric” (memory controller & PCIe)
- 8 channels of DDR4-3200 per IO device
  - MemBW: 8 ch x 8 byte x 3.2 GHz = 204.8 GB/s
- ccNUMA feature (boot time option):
  - Nodes Per Socket (NPS)=1 , 2 or 4
  - **NPS=4 → 4 ccNUMA domains**

Socket



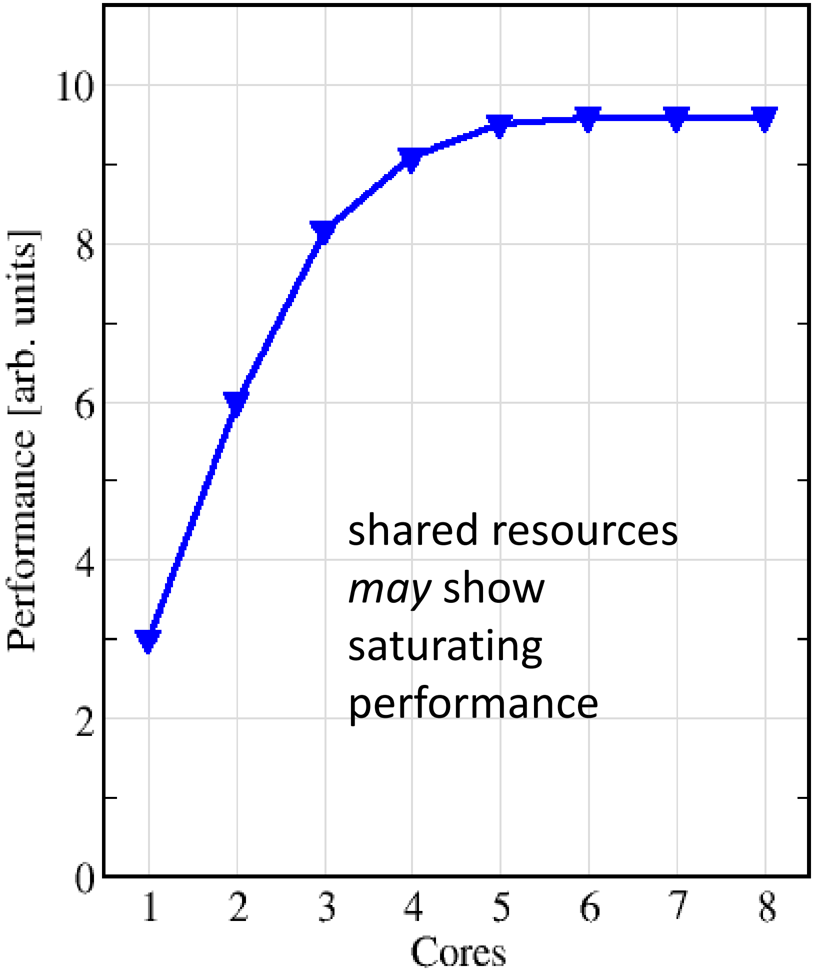
Adding accelerators to the node



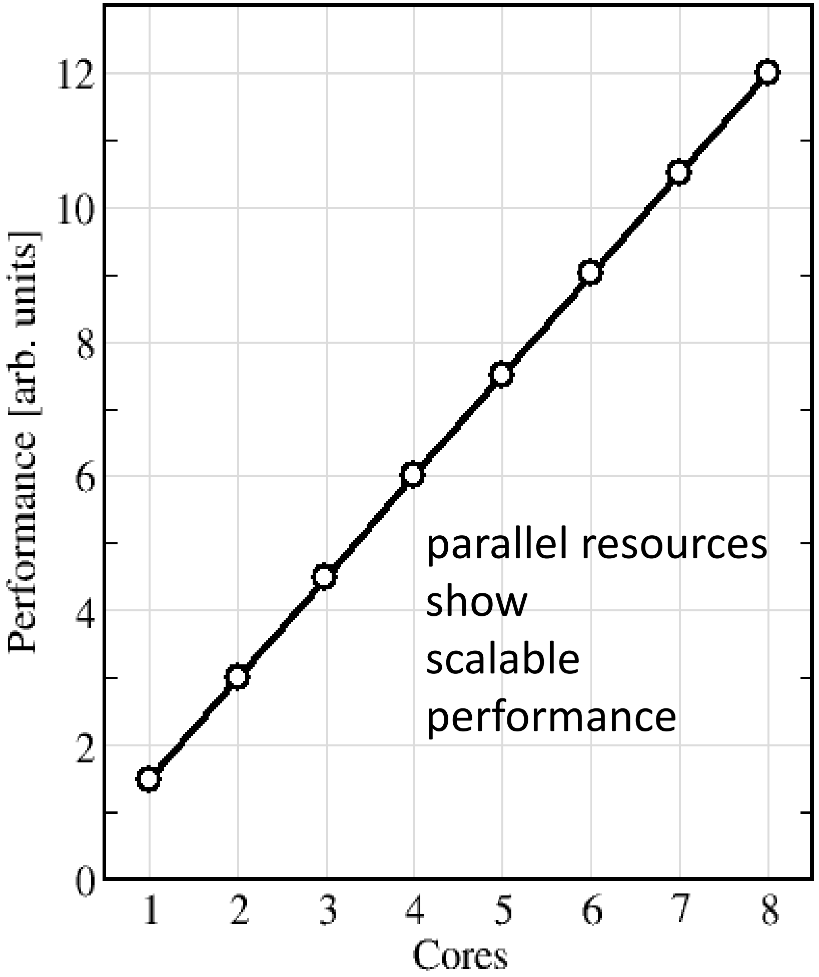
Scalable and saturating behavior

Clearly distinguish between “**saturating**” and “**scalable**” performance on the chip level

One of the most important performance signatures



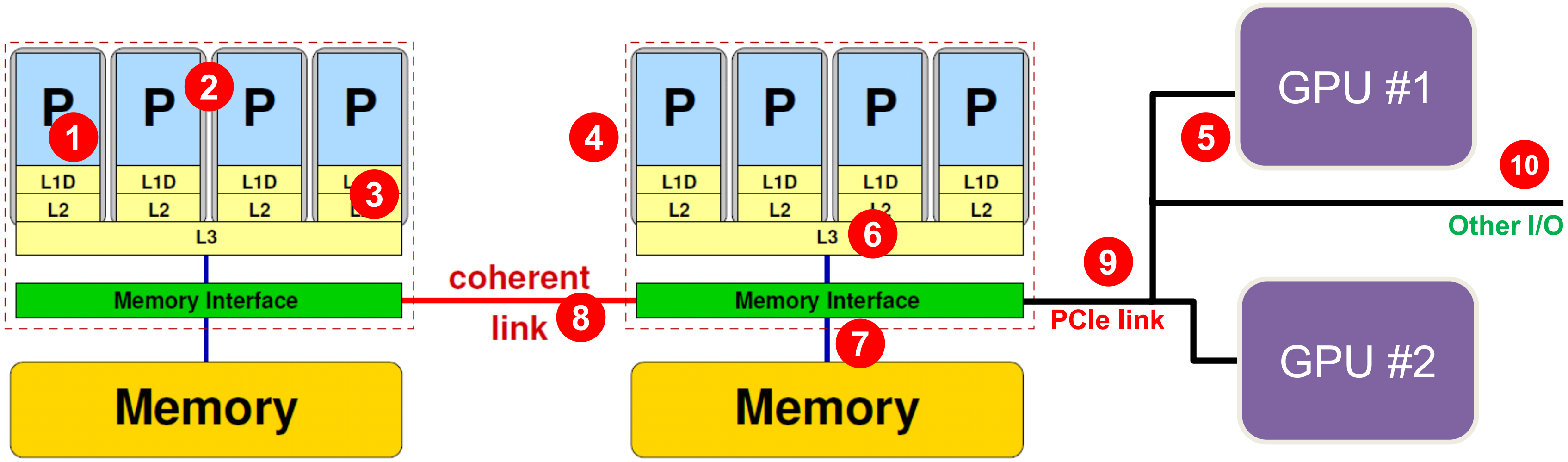
shared resources *may* show saturating performance



parallel resources show scalable performance

Parallelism in a modern compute node

Parallel and shared resources within a shared-memory node



Parallel resources:

- Execution/SIMD units 1
- Cores 2
- Inner cache levels 3
- Sockets / ccNUMA domains 4
- Multiple accelerators 5

Shared resources:

- Outer cache level per socket 6
- Memory bus per socket 7
- Intersocket link 8
- PCIe bus(es) 9
- Other I/O resources 10

How does your application react to all of those details?

Interlude:
A glance at accelerator technology

NVIDIA “Ampere” A100

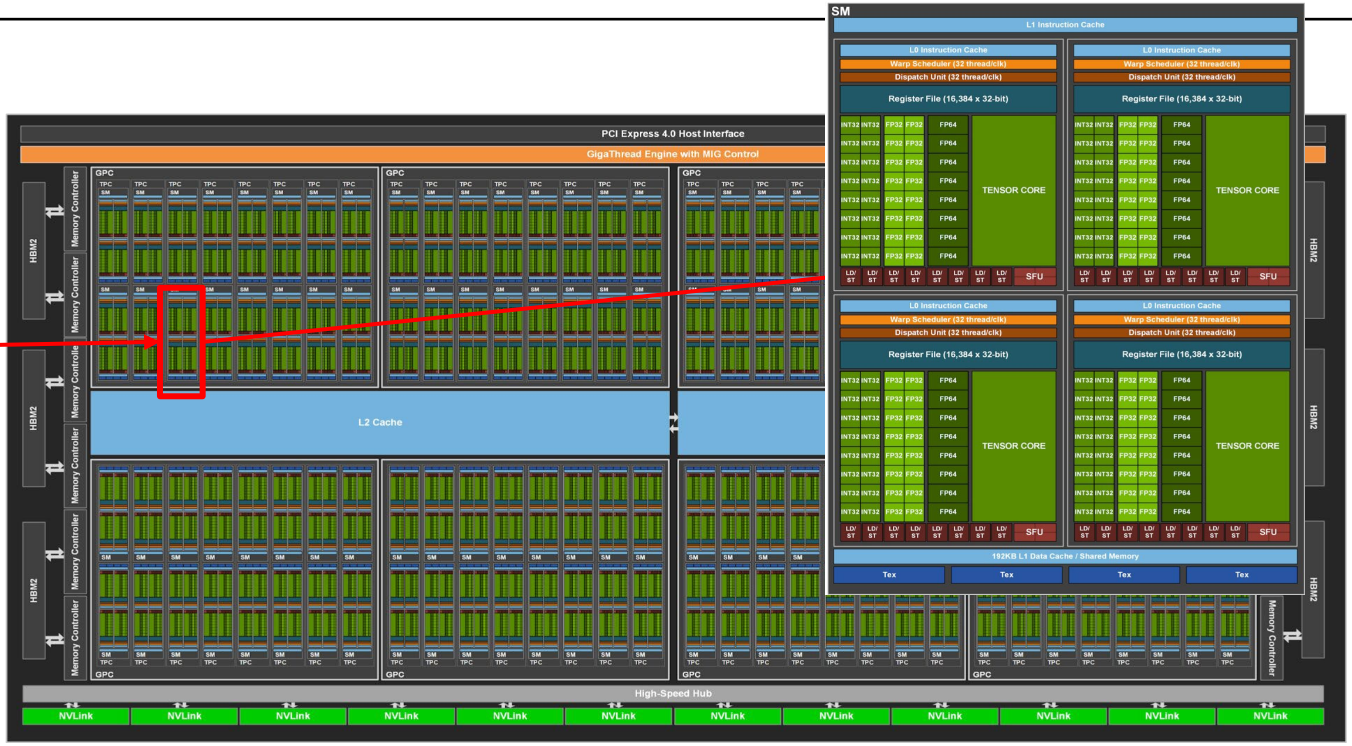
vs.

AMD Zen2 “Rome”

Nvidia A100 "Ampere" SXM4 specs

Architecture

- 54.2 B Transistors
- ~ 1.4 GHz clock speed
- ~ 108 "SM" units
  - 64 SP "cores" each (FMA)
  - 32 DP "cores" each (FMA)
  - 4 "Tensor Cores" each
  - 2:1 SP:DP performance


SM
L1 Instruction Cache
L0 Instruction Cache
Warp Scheduler (32 thread/clk)
Dispatch Unit (32 thread/clk)
Register File (16,384 x 32-bit)
INT32
FP32
FP64
TENSOR CORE
LD/ST
SFU
192KB L1 Data Cache / Shared Memory
Tex
PCI Express 4.0 Host Interface
GigaThread Engine with MIG Control
GPC
TPC
SM
L2 Cache
Memory Controller
HBM2
High-Speed Hub
NVLink

© Nvidia

- 9.7 TFlop/s DP peak (FP64)
- 40 MiB L2 Cache

- 40 GB (5120-bit) HBM2
- MemBW ~ 1555 GB/s (theoretical)
- MemBW ~ 1400 GB/s (measured)

$$P_{peak}^{DP} = n_{SM} \cdot n_{core} \cdot n_{FP} \cdot f$$

# SMs

CUDA cores/SM

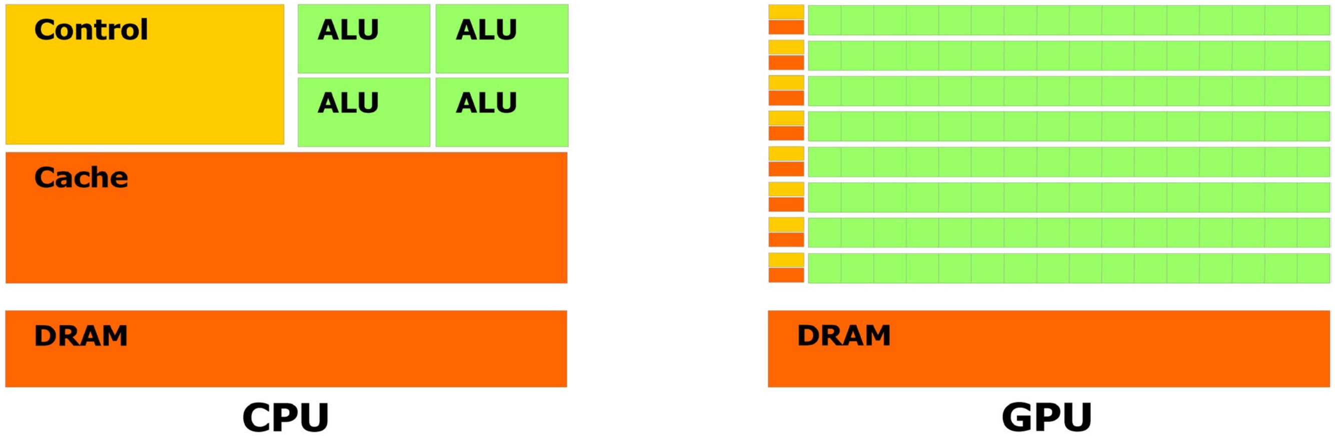
# FP ops/cy

$$n_{SM} = 108$$
$$n_{core} = 32$$
$$n_{FP} = 2\frac{\text{flops}}{\text{cy}}$$
$$f = 1.4\frac{\text{Gcy}}{\text{s}}$$

Trading single thread performance for parallelism: *GPGPUs vs. CPUs*

GPU vs. CPU

light speed estimate



	2 x AMD EPYC 7742 ”Rome”	NVidia Tesla A100 “Ampere”
Cores@Clock	2 x 64 @ 2.25 GHz	108 SMs @ ~1.4 GHz
FP32 Performance/core	72 GFlop/s	~179 GFlop/s
Threads@STREAM	~16	~ 100000
FP32 peak	9.2 TFlop/s	~19.5 TFlop/s
Stream BW (meas.)	2 x 180 GB/s	1400 GB/s
Transistors / TDP	~2x40 Billion / 2x225 W	54 Billion/400 W

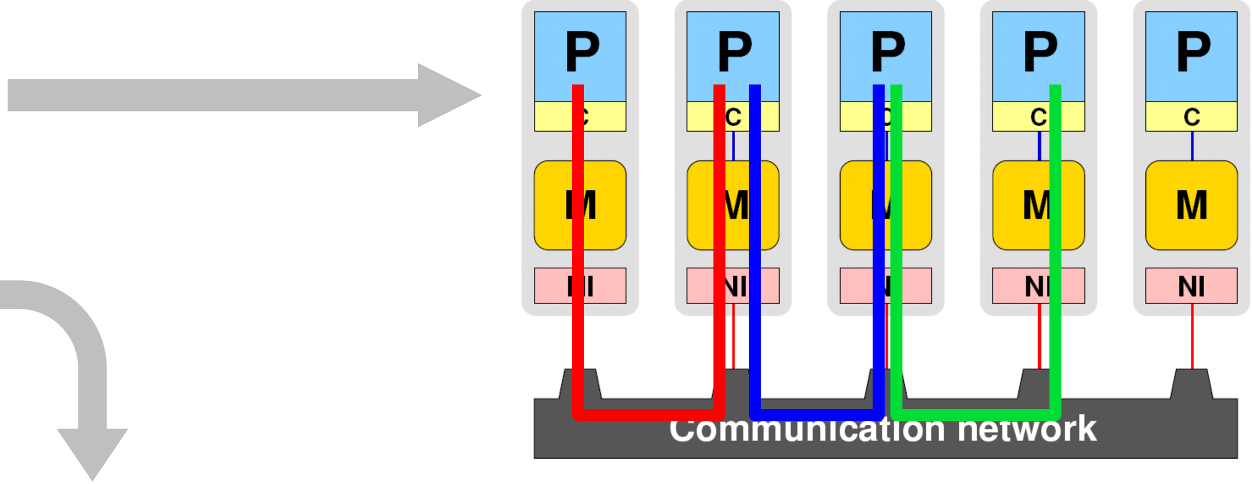
~2x

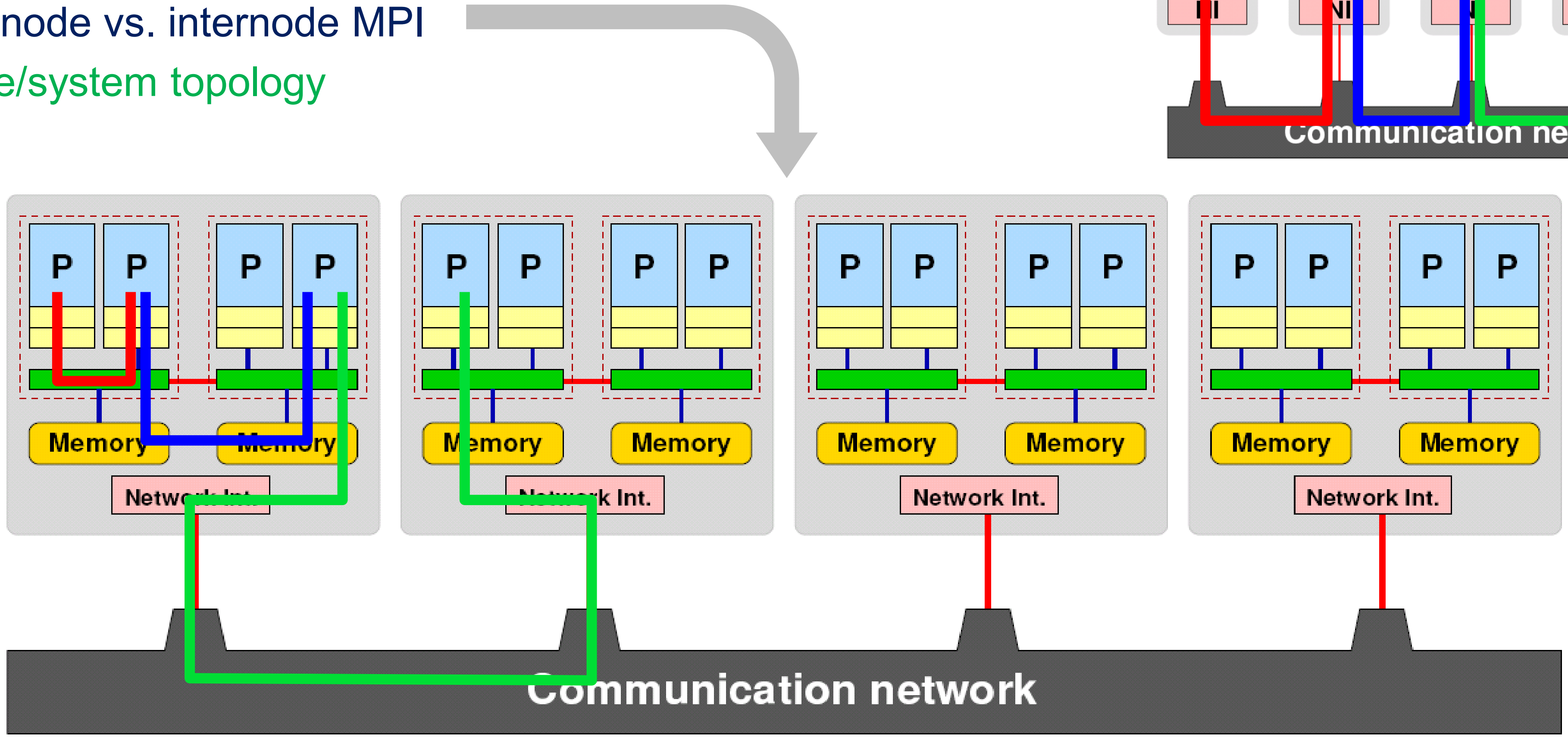
~4x

Node topology and programming models

Parallel programming models: Pure MPI

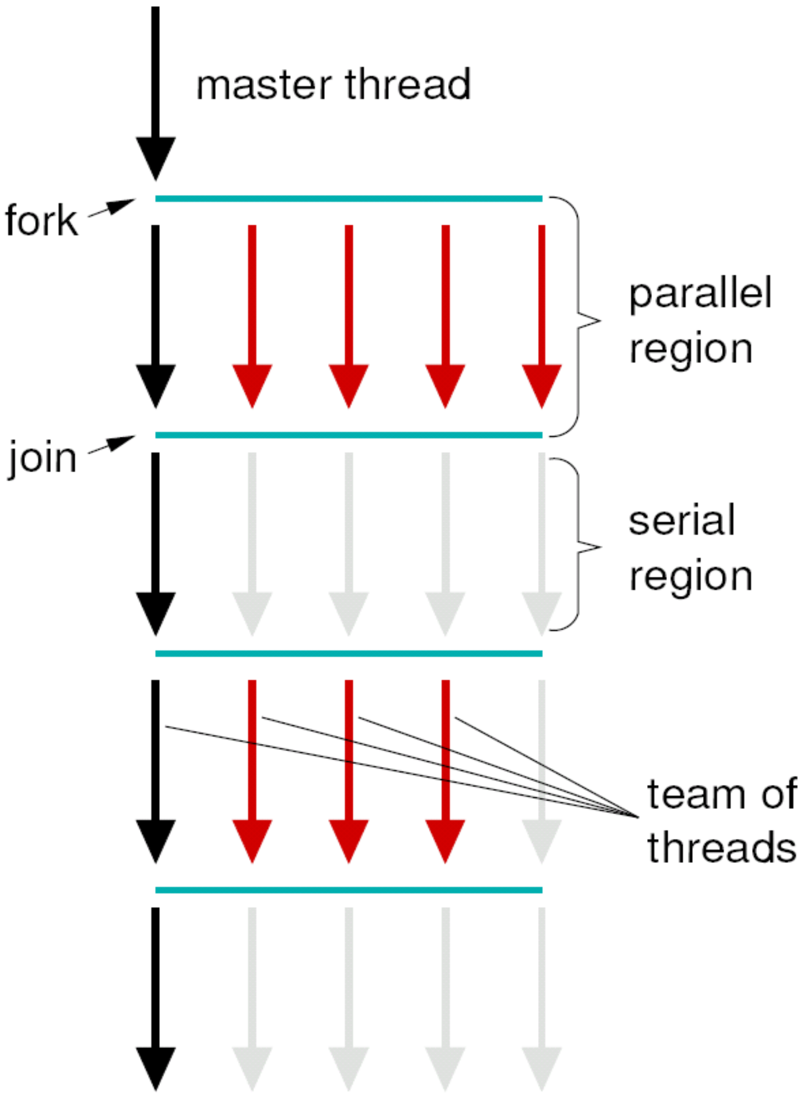
- **Machine structure is invisible to user:**
  - → Very simple programming model
  - → MPI "knows what to do"!?
- **Performance issues**
  - Intranode vs. internode MPI
  - Node/system topology

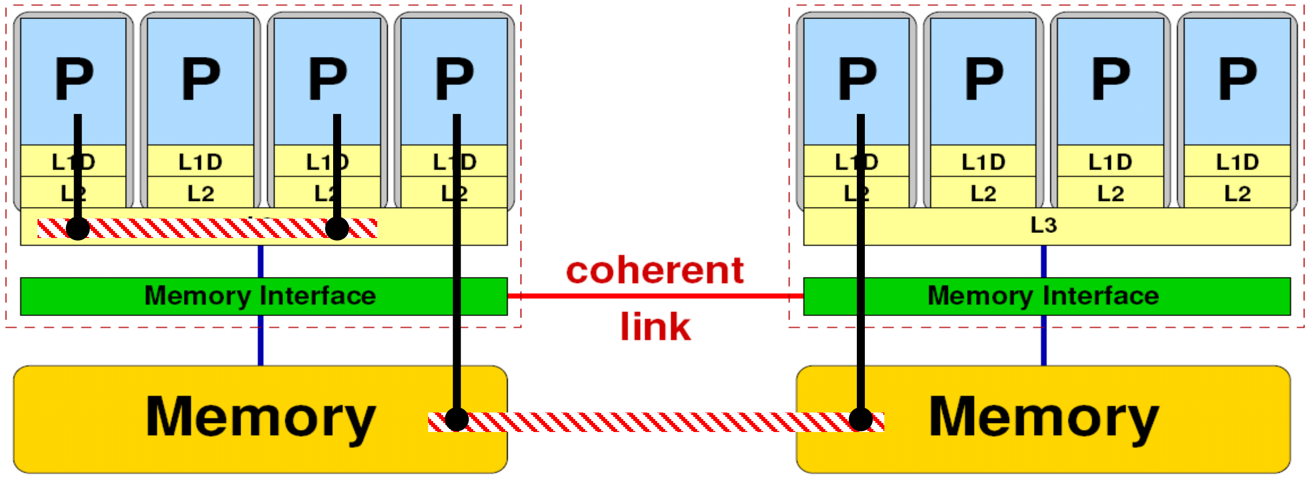




Parallel programming models: Pure threading

- **Machine structure is invisible to user**
  - Very simple programming model
  - Threading SW (OpenMP, pthreads, TBB,…) “should” know about the details
  - OpenMP 4++: some support
  - Performance issues
  - Synchronization overhead
  - Memory access
  - Node topology





Conclusions about architecture

- Performance is a result of
  - How **many instructions** you require to implement an algorithm
  - How **efficiently** those instructions are **executed** on a processor
  - Runtime contribution of the triggered **data transfers**
- Modern computer architecture has a rich “topology”
- Node-level hardware parallelism takes many forms
  - Sockets/devices – CPU: 1-4 or more, GPGPU: 1-8
  - Cores – moderate (CPU: 20-128, GPGPU: 10-100)
  - SIMD – moderate (CPU: 2-16) to massive (GPGPU: 10’s-100’s)
  - Superscalarity (CPU: 2-6)
- Performance of programs is sensitive to architecture
  - Topology/affinity influences overheads of popular programming models
  - Standards do not contain (many) topology-aware features
    - Things are starting to improve slowly (MPI 3.0, OpenMP 4.0)
  - Apart from overheads, performance features are largely independent of the programming model