

# Node-Level Performance Engineering

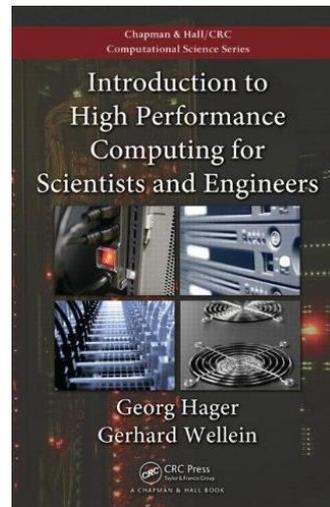
Georg Hager, Jan Treibig, Gerhard Wellein  
Erlangen Regional Computing Center (RRZE)  
University of Erlangen-Nuremberg

PPAM 2013 tutorial  
September 8, 2013  
Warsaw, Poland





- Where can I find these *gorgeous* slides?
- Other information?
  - <http://blogs.fau.de/hager>
- Anything else?



ISBN 978-1439811924



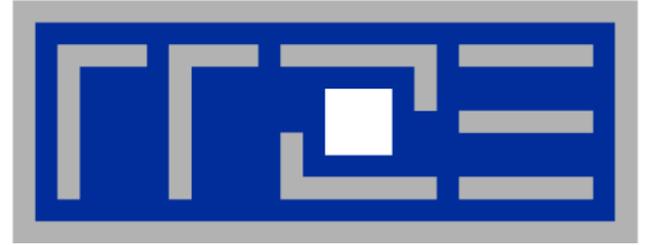
<http://goo.gl/eocNpa>



- **Preliminaries**
- **Introduction to multicore architecture**
  - Cores, caches, chips, sockets, ccNUMA, SIMD
- **LIKWID tools**
- **Microbenchmarking for architectural exploration**
  - Streaming benchmarks: throughput mode
  - Streaming benchmarks: work sharing
  - Roadblocks for scalability: Saturation effects and OpenMP overhead
- **Node-level performance modeling**
  - The Roofline Model
  - Case study: 3D Jacobi solver and model-guided optimization
- **Optimal resource utilization**
  - SIMD parallelism
  - ccNUMA



- **Preliminaries**
- **Introduction to multicore architecture**
  - Cores, caches, chips, sockets, ccNUMA, SIMD
- **LIKWID tools**
- **Microbenchmarking for architectural exploration**
  - Streaming benchmarks: throughput mode
  - Streaming benchmarks: work sharing
  - Roadblocks for scalability: Saturation effects and OpenMP overhead
- **Node-level performance modeling**
  - The Roofline Model
  - Case study: 3D Jacobi solver and model-guided optimization
- **Optimal resource utilization**
  - SIMD parallelism
  - ccNUMA



**Prelude:**  
**Scalability 4 teh win!**



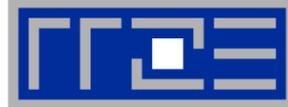
## **Lore 1**

**In a world of highly parallel computer architectures only highly scalable codes will survive**

## **Lore 2**

**Single core performance no longer matters since we have so many of them and use scalable codes**

# Scalability Myth: Code scalability is the key issue



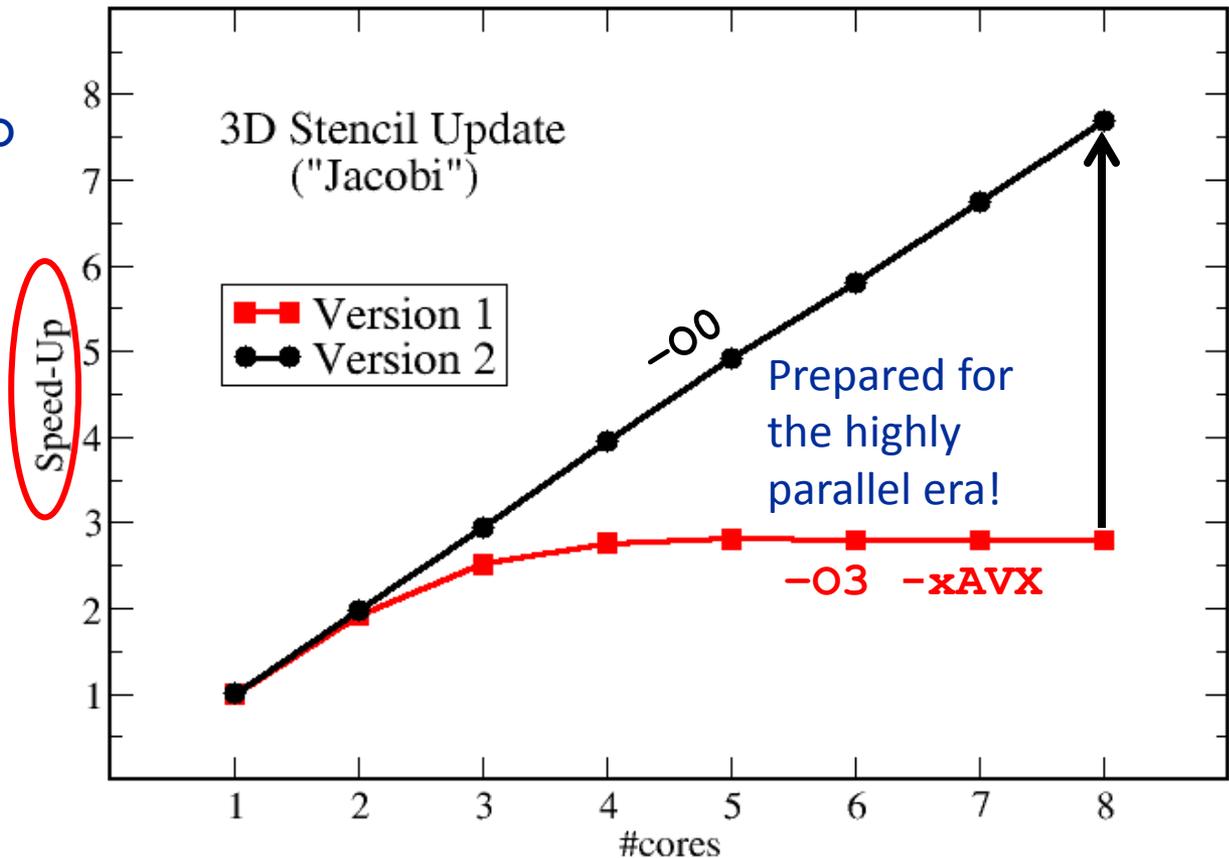
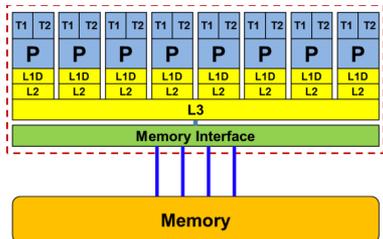
```

!$OMP PARALLEL DO
do k = 1 , Nk
  do j = 1 , Nj; do i = 1 , Ni
    y(i,j,k) = b* ( x(i-1,j,k)+ x(i+1,j,k)+ x(i,j-1,k)+
                   x(i,j+1,k)+ x(i,j,k-1)+ x(i,j,k+1))
  enddo; enddo
enddo
!$OMP END PARALLEL DO
    
```

```

enddo; enddo
enddo
!$OMP END PARALLEL DO
    
```

Changing only the compile options makes this code scalable on an 8-core chip



# Scalability Myth: Code scalability is the key issue

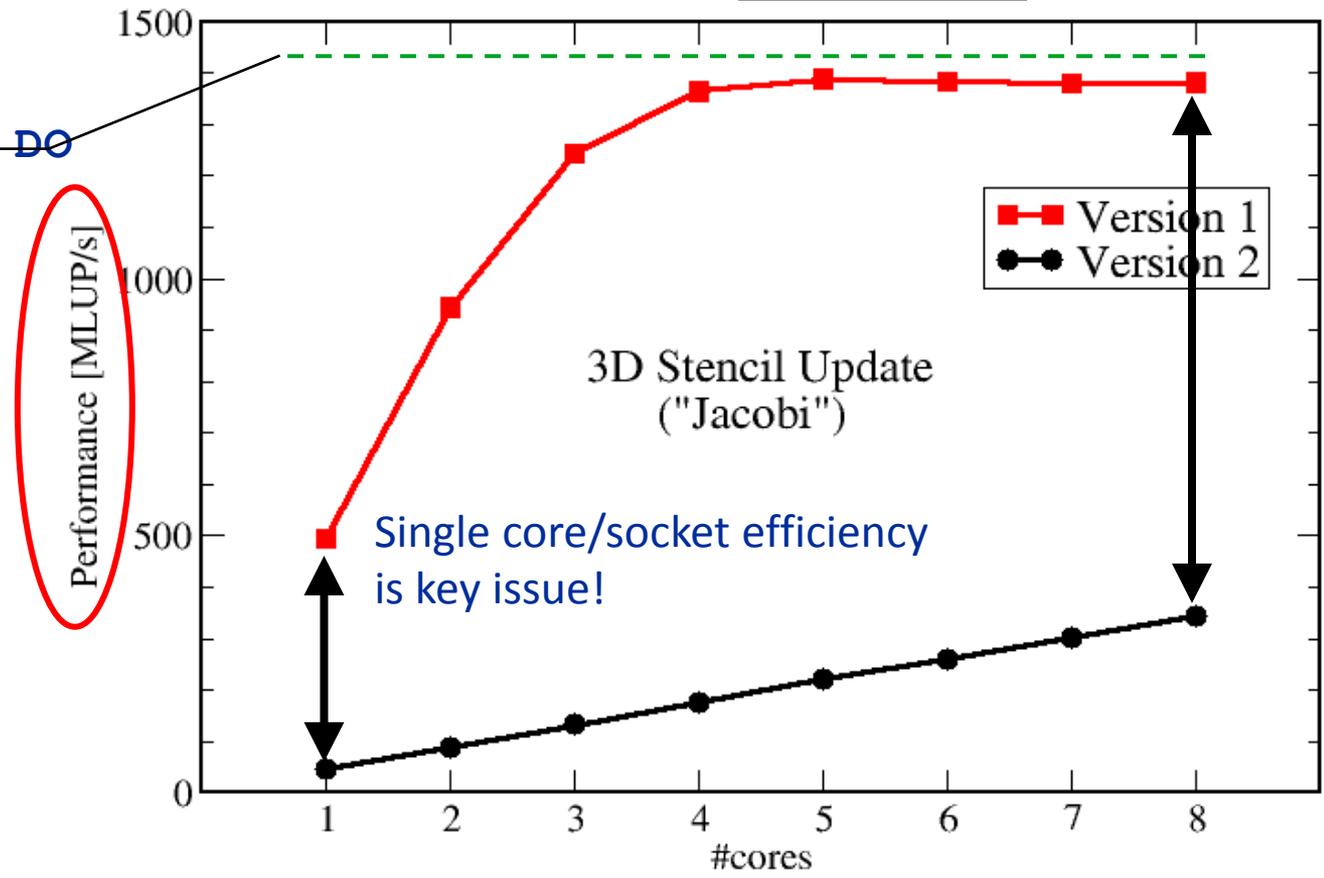
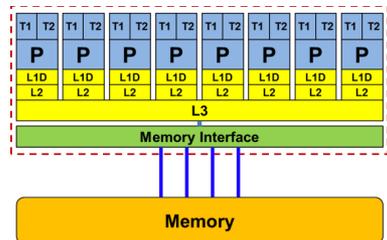


```

!$OMP PARALLEL DO
do k = 1 , Nk
  do j = 1 , Nj; do i = 1 , Ni
    y(i,j,k) = b*( x(i-1,j,k)+ x(i+1,j,k)+ x(i,j-1,k)+
      x(i,j+1,k)+ x(i,j,k-1)+ x(i,j,k+1))
  enddo; enddo
enddo

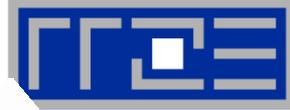
```

Upper limit from simple performance model:  
35 GB/s & 24 Byte/update





- **Do I understand the performance behavior of my code?**
  - Does the performance **match a model** I have made?
- **What is the optimal performance for my code on a given machine?**
  - **High Performance Computing == Computing at the bottleneck**
- **Can I change my code so that the “optimal performance” gets higher?**
  - Circumventing/ameliorating the impact of the bottleneck
- **My model does not work – what’s wrong?**
  - **This is the good case**, because you learn something
  - Performance monitoring / microbenchmarking may help clear up the situation



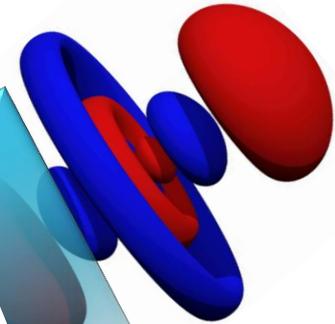
## Newtonian mechanics



$$\vec{F} = m\vec{a}$$

**Fails @ small scales!**

## Nonrelativistic quantum mechanics

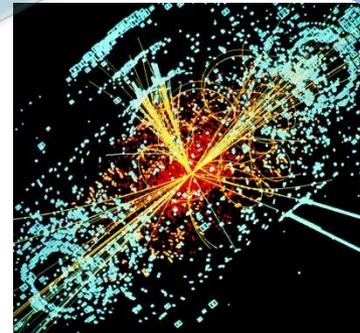


$$i\hbar \frac{\partial}{\partial t} \psi(\vec{r}, t) = H\psi(\vec{r}, t)$$

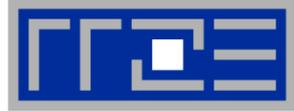
**Fails @ even smaller scales!**

**If a model fails,  
we learn something!**

## Relativistic quantum field theory

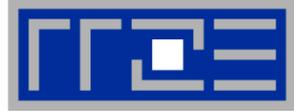


$$U(1)_Y \otimes SU(2)_L \otimes SU(3)_c$$

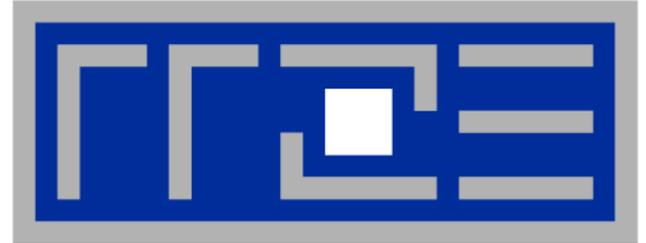


**There is no alternative to knowing what is going on  
between your code and the hardware**

**Without performance modeling,  
optimizing code is like stumbling in the dark**



- Preliminaries
- **Introduction to multicore architecture**
  - Cores, caches, chips, sockets, ccNUMA, SIMD
- LIKWID tools
- **Microbenchmarking for architectural exploration**
  - Streaming benchmarks: throughput mode
  - Streaming benchmarks: work sharing
  - Roadblocks for scalability: Saturation effects and OpenMP overhead
- **Node-level performance modeling**
  - The Roofline Model
  - Case study: 3D Jacobi solver and model-guided optimization
- **Optimal resource utilization**
  - SIMD parallelism
  - ccNUMA



# **Introduction: Modern node architecture**

**Multi- and manycore chips and nodes**

**A glance at basic core features**

**Caches and data transfers through the memory hierarchy**

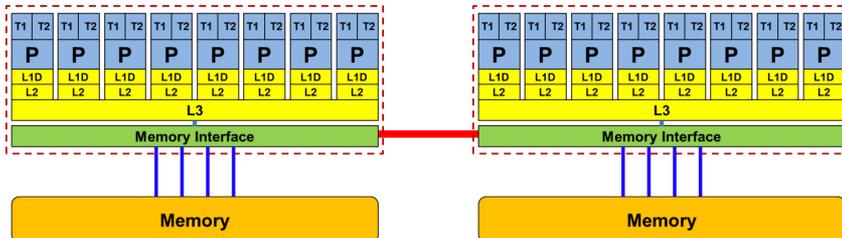
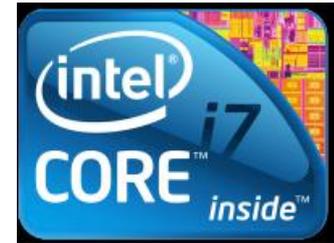
**Memory organization**

**Accelerators**

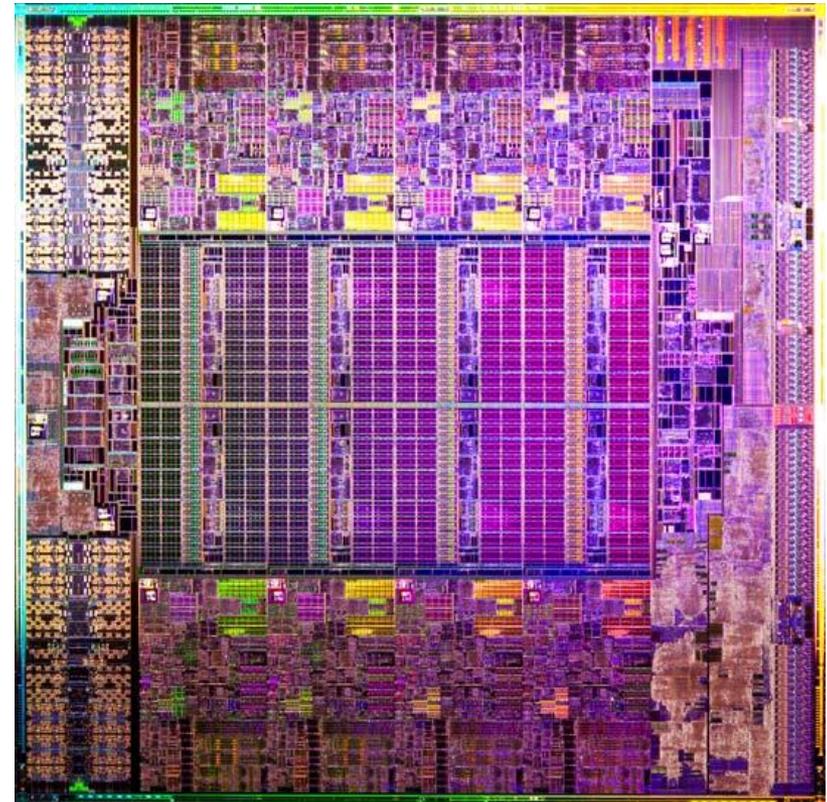
# Multi-Core: Intel Xeon 2600 (2012)



- Xeon 2600 “Sandy Bridge EP”:  
8 cores running at 2.7 GHz (max 3.2 GHz)
- Simultaneous Multithreading  
→ reports as 16-way chip
- **2.3 Billion** Transistors / 32 nm
- Die size: 435 mm<sup>2</sup>

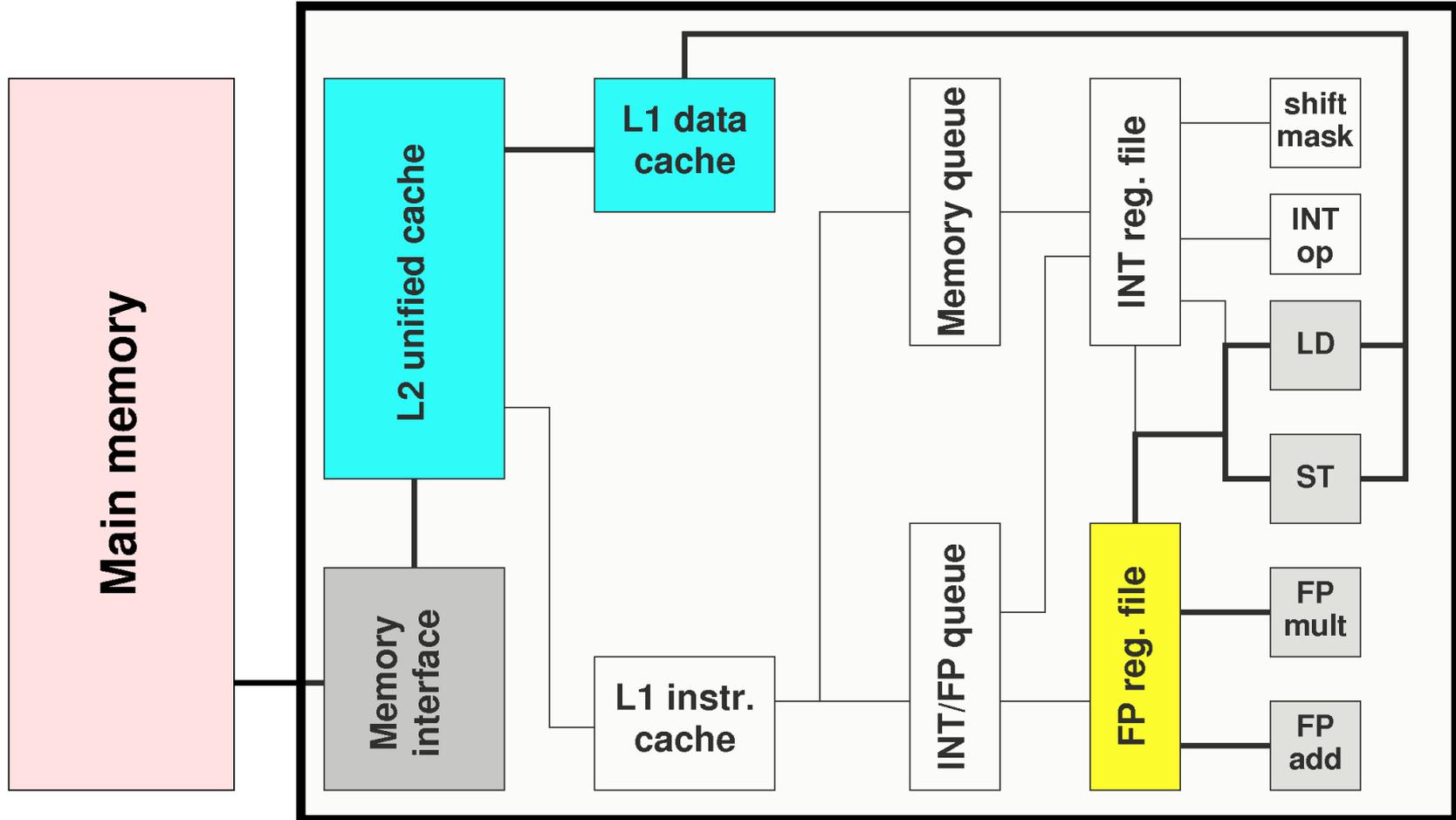


2-socket server





- (Almost) the same basic design in all modern systems

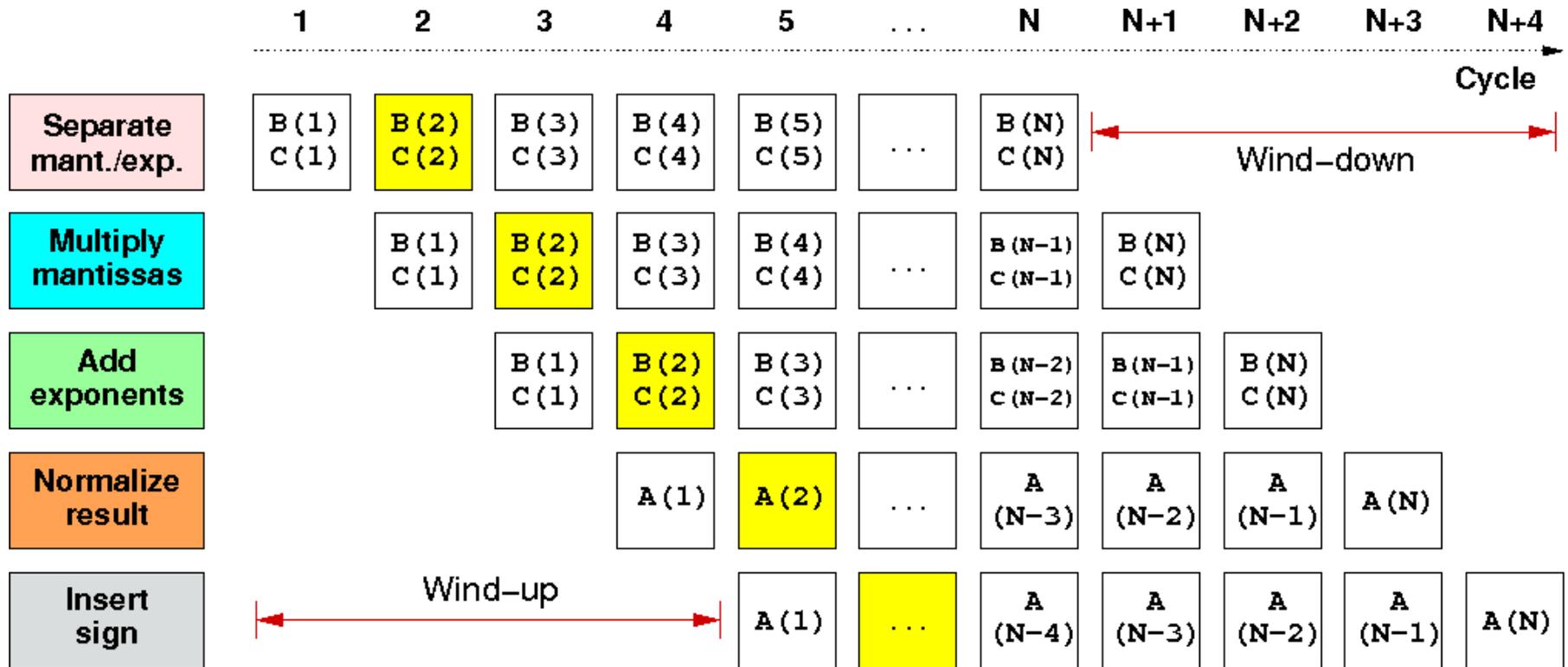


Not shown: most of the control unit, e.g. instruction fetch/decode, branch prediction,...



- **Idea:**
  - Split complex instruction into several simple / fast steps (stages)
  - Each step takes the same amount of time, e.g. a single cycle
  - Execute different steps on different instructions at the same time (in parallel)
- **Allows for shorter cycle times (simpler logic circuits), e.g.:**
  - floating point multiplication takes 5 cycles, but
  - processor can work on 5 different multiplications simultaneously
  - one result at each cycle after the pipeline is full
- **Drawback:**
  - Pipeline must be filled - startup times ( $\#Instructions \gg$  pipeline steps)
  - Efficient use of pipelines requires large number of independent instructions → instruction level parallelism
  - Requires complex instruction scheduling by compiler/hardware – software-pipelining / out-of-order
- **Pipelining is widely used in modern computer architectures**

# 5-stage Multiplication-Pipeline: $A(i)=B(i)*C(i)$ ; $i=1,\dots,N$

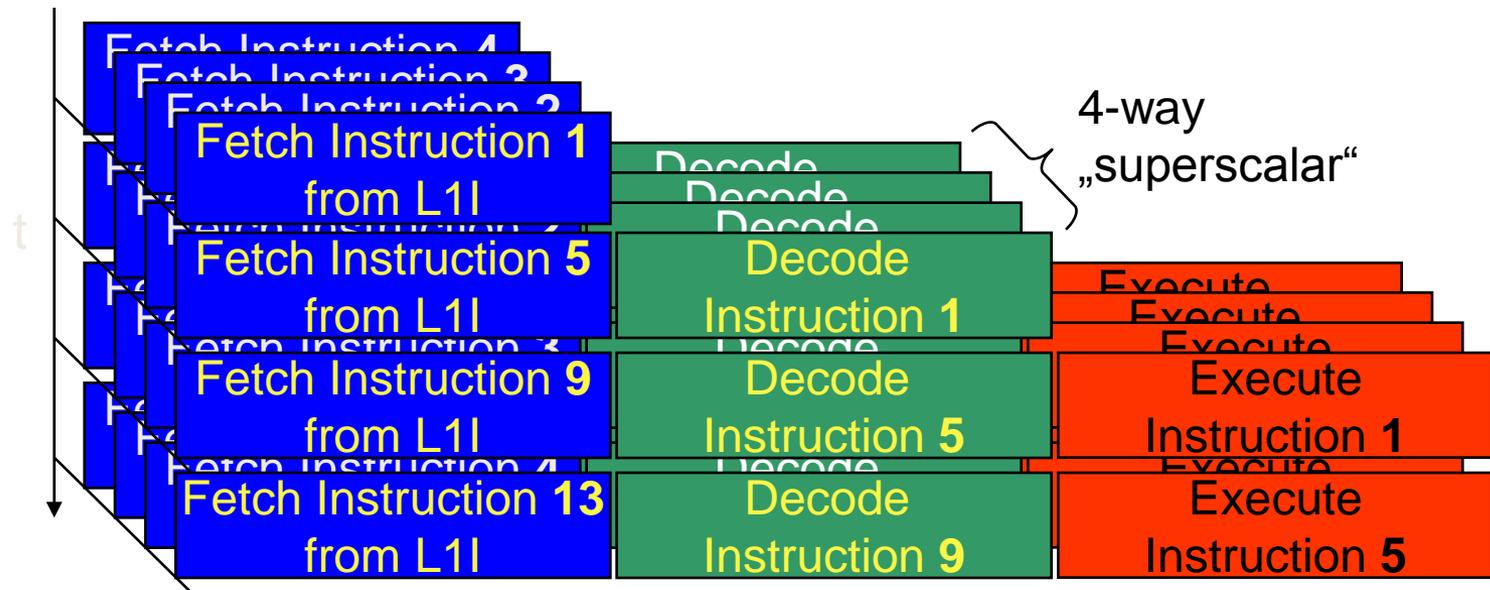


First result is available after 5 cycles (=latency of pipeline)!

Wind-up/-down phases: Empty pipeline stages



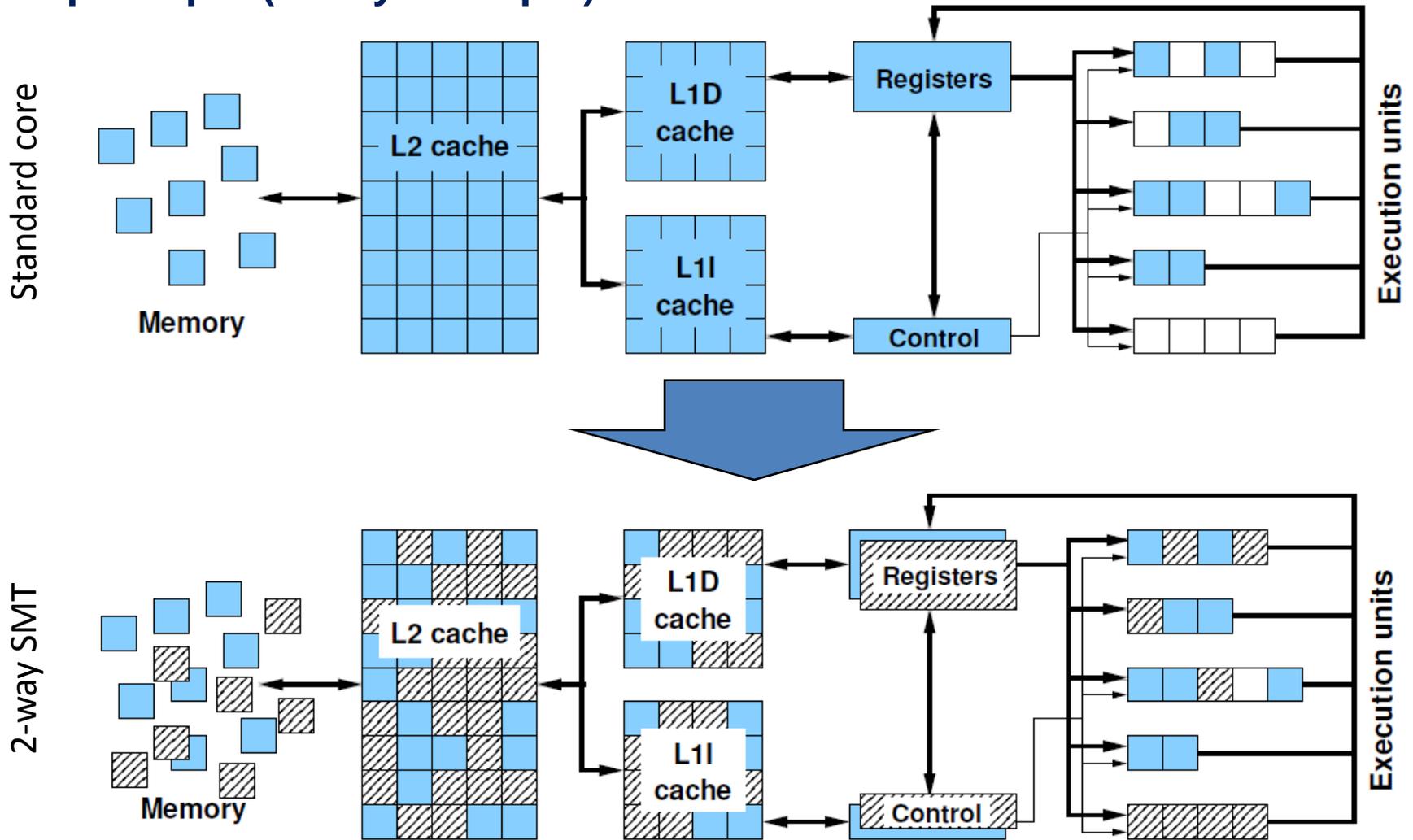
- Multiple units enable use of **I**nstruction **L**evel **P**arallelism (ILP):  
Instruction stream is “parallelized” on the fly



- Issuing  $m$  concurrent instructions per cycle:  $m$ -way superscalar
- Modern processors are 3- to 6-way superscalar & can perform 2 or 4 floating point operations per cycles

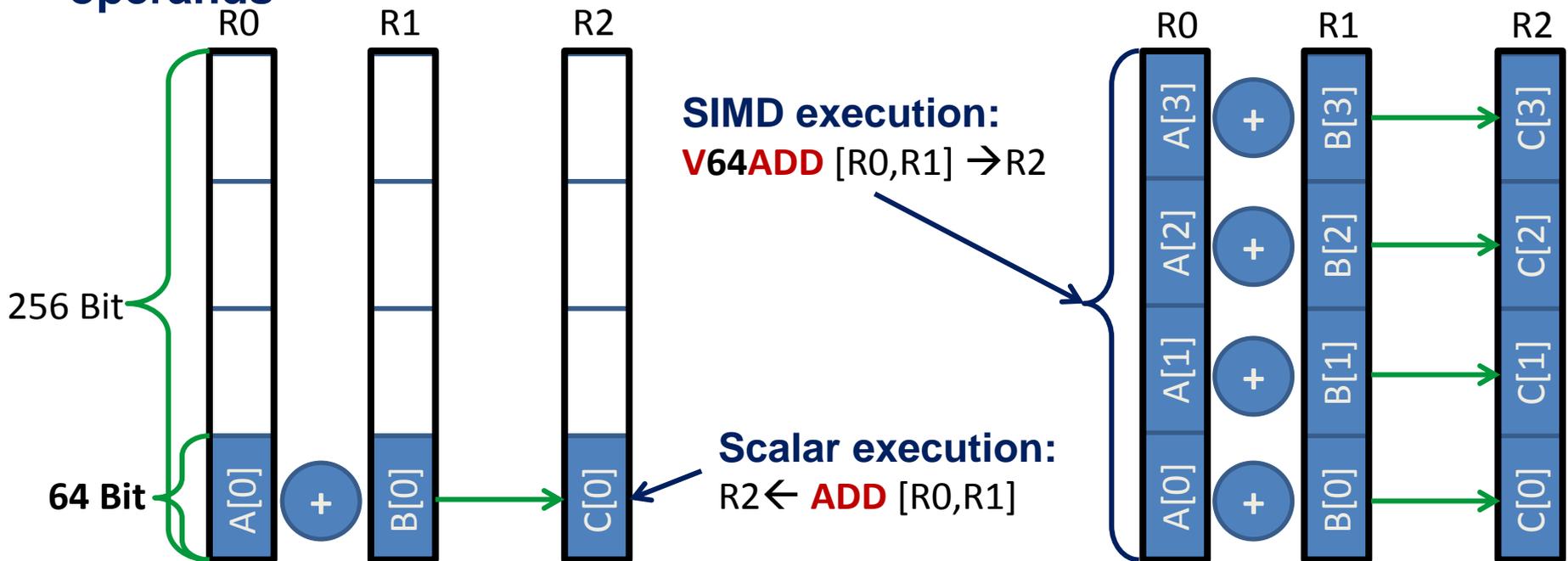


## SMT principle (2-way example):



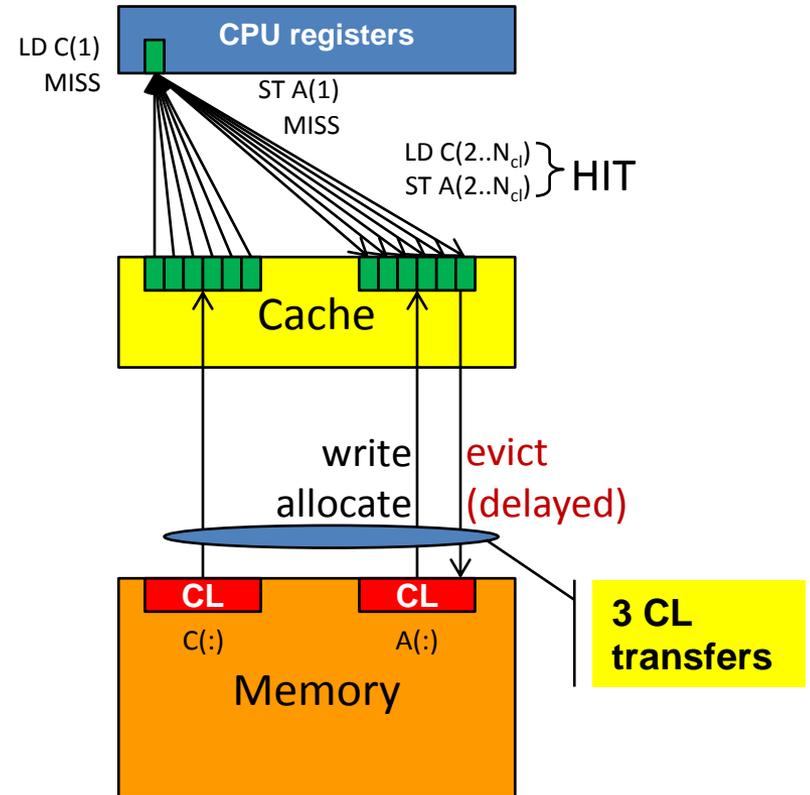


- **Single Instruction Multiple Data (SIMD)** operations allow the **concurrent execution of the same operation on “wide” registers**
- **x86 SIMD instruction sets:**
  - SSE: register width = 128 Bit → 2 double precision floating point operands
  - AVX: register width = 256 Bit → 4 double precision floating point operands
- **Adding two registers holding double precision floating point operands**



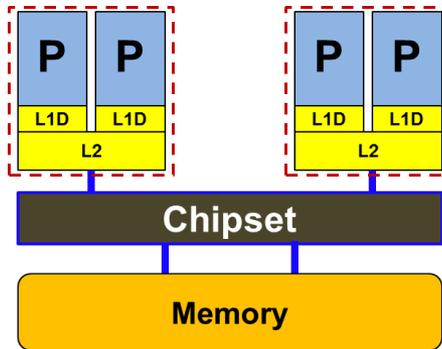


- How does data travel from memory to the CPU and back?
- Remember: Caches are organized in **cache lines** (e.g., 64 bytes)
- Only **complete cache lines** are transferred between memory hierarchy levels (except registers)
- MISS**: Load or store instruction does not find the data in a cache level → CL transfer required
- Example: Array copy  $A(:) = C(:)$





### Yesterday (2006): Dual-socket Intel “Core2” node:

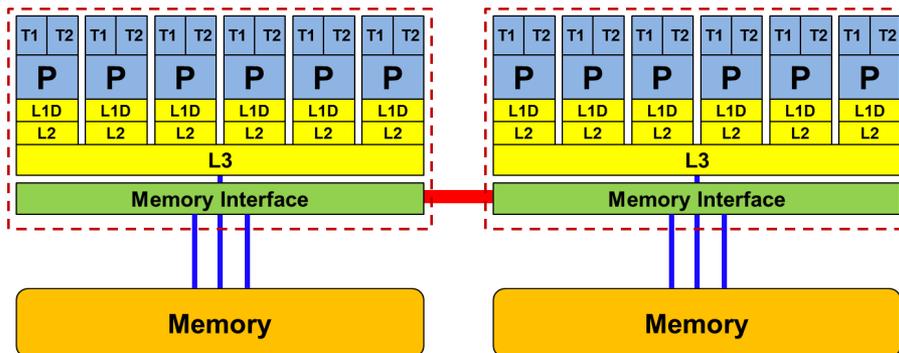


Uniform Memory Architecture (UMA)

Flat memory ; symmetric MPs

But: system “anisotropy”

### Today: Dual-socket Intel (Westmere,...) node:



Cache-coherent Non-Uniform Memory Architecture (**ccNUMA**)

**HT / QPI** provide scalable bandwidth at the price of ccNUMA architectures: *Where does my data finally end up?*

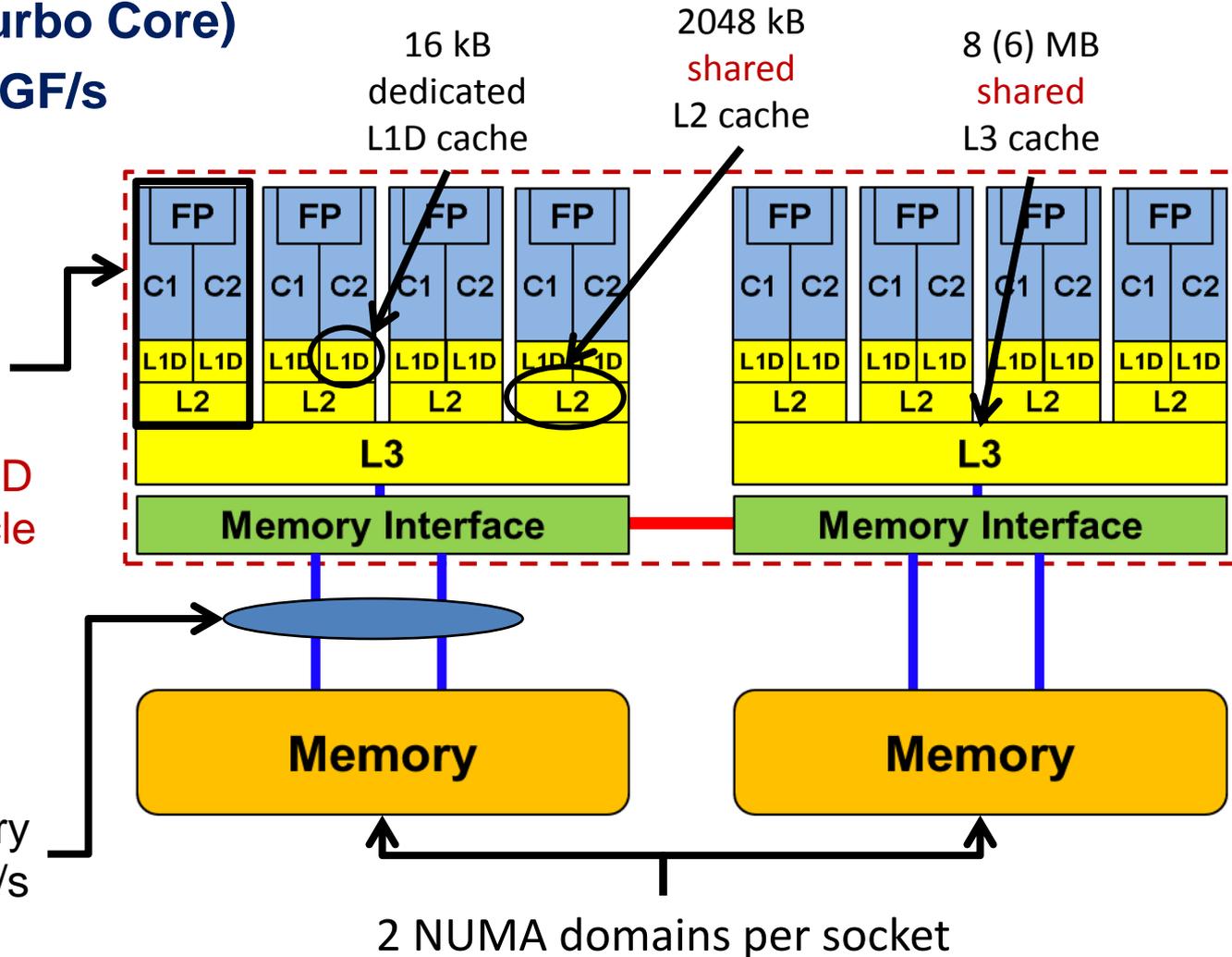
**On AMD it is even more complicated → ccNUMA within a socket!**



- **Up to 16 cores (8 Bulldozer modules) in a single socket**
- **Max. 2.6 GHz (+ Turbo Core)**
- $P_{max} = (2.6 \times 8 \times 8) \text{ GF/s}$   
 $= 166.4 \text{ GF/s}$

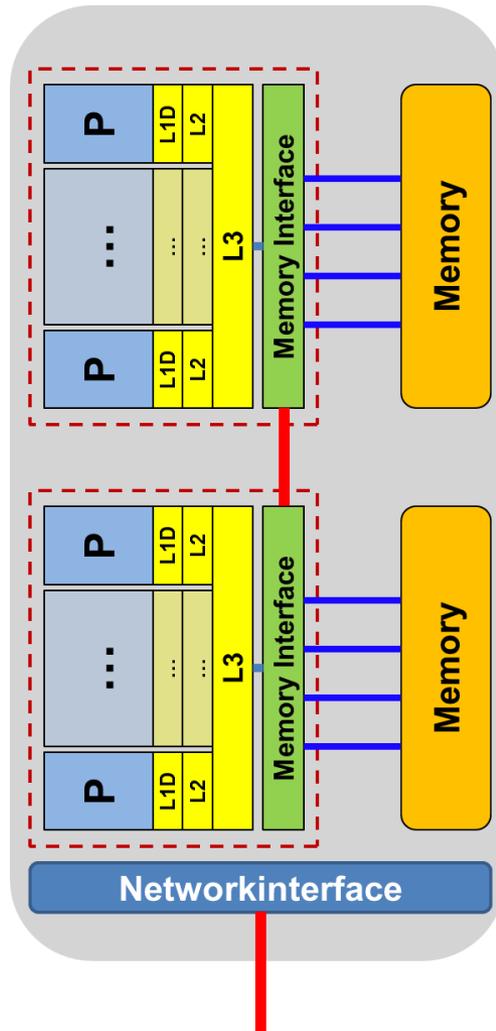
Each Bulldozer module:

- 2 “lightweight” cores
- **1 FPU: 4 MULT & 4 ADD (double precision) / cycle**
- Supports AVX
- Supports FMA4



2 DDR3 (**shared**) memory channels > 15 GB/s

2 NUMA domains per socket



- **8 cores per socket 2.7 GHz (3.5 @ turbo)**
- **DDR3 memory interface with 4 channels per chip**
- **Two-way SMT**
- **Two 256-bit SIMD FP units**
  - SSE4.2, AVX
- **32 kB L1 data cache per core**
- **256 kB L2 cache per core**
- **20 MB L3 cache per chip**

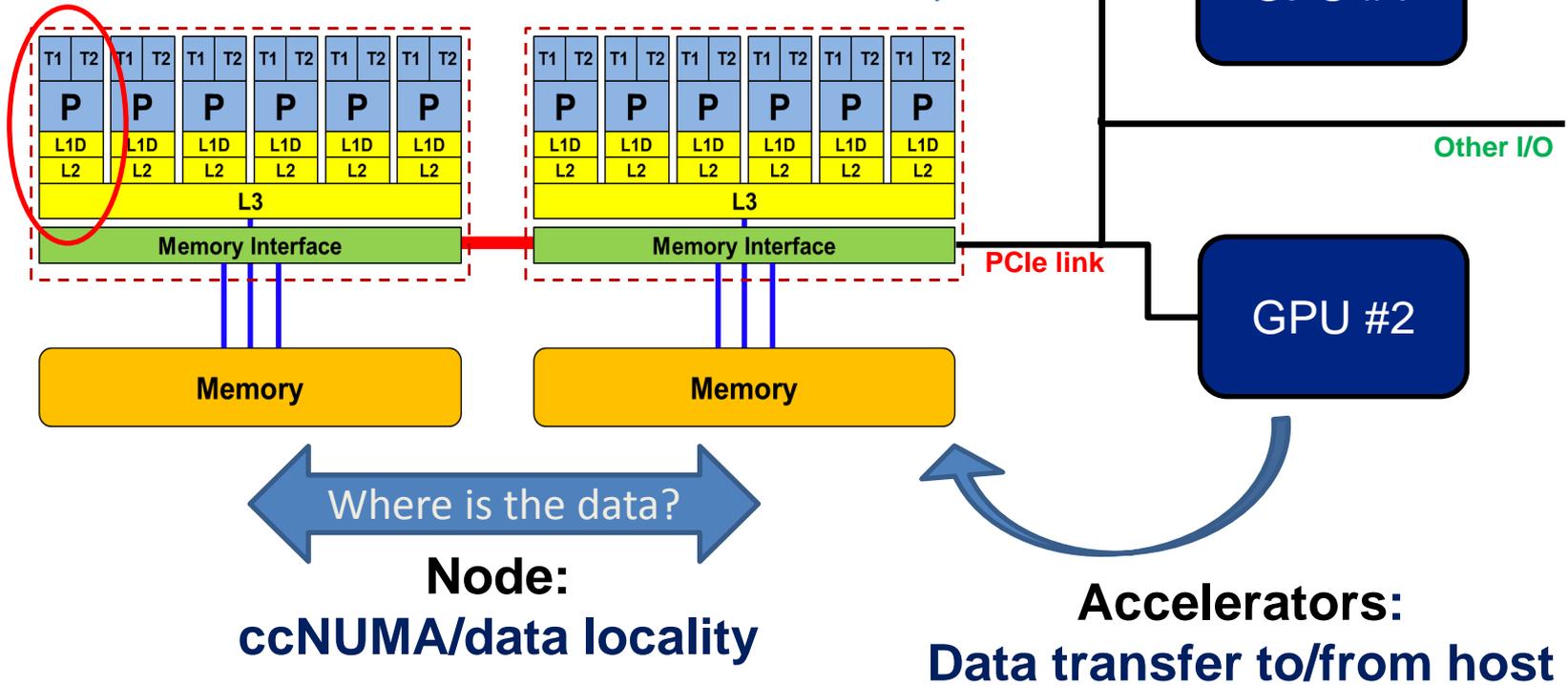




**Heterogeneous programming is here to stay!**  
**SIMD + OpenMP + MPI + CUDA, OpenCL,...**

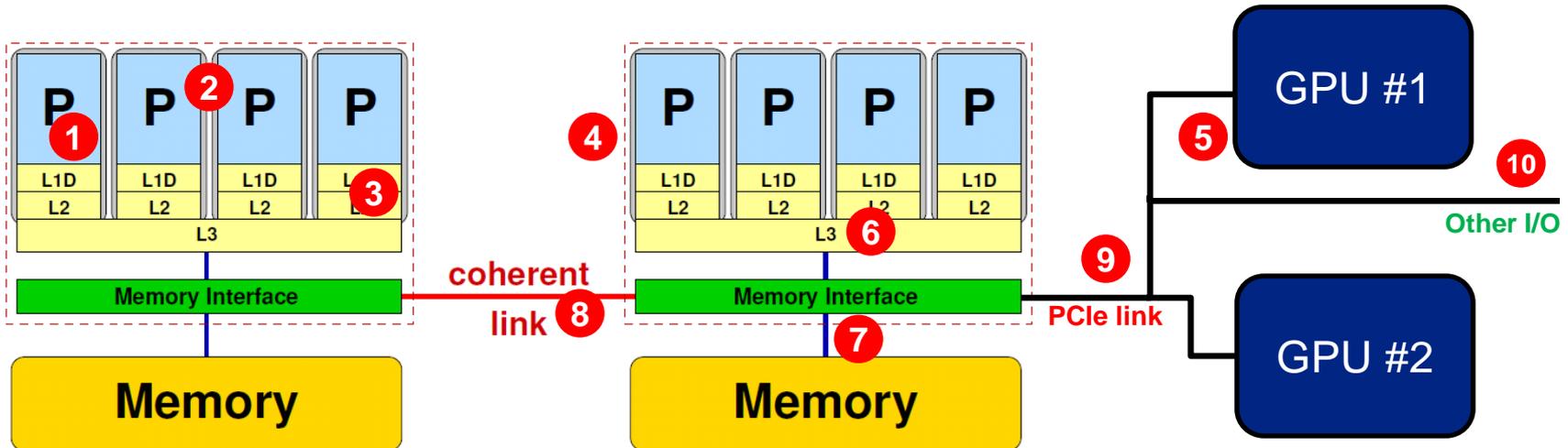
**Core:**  
SIMD vectorization  
SMT

**Socket:**  
Parallelization  
Shared Resources





- Parallel and shared resources within a shared-memory node



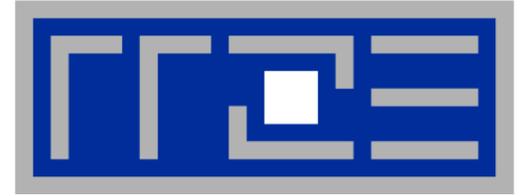
## Parallel resources:

- 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?**



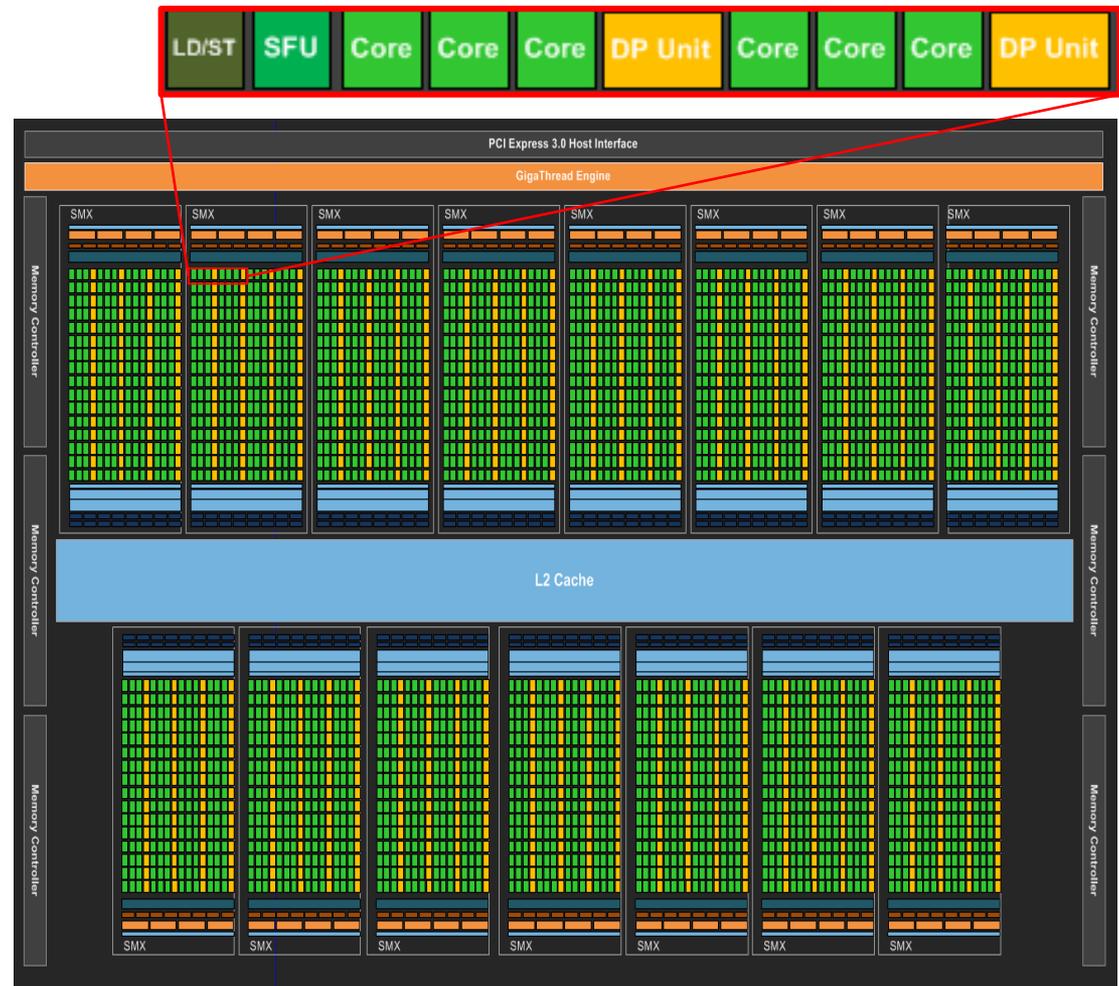
**Interlude:**  
**A glance at current accelerator technology**

# NVIDIA Kepler GK110 Block Diagram



## Architecture

- 7.1B Transistors
- 15 “SMX” units
  - 192 (SP) “cores” each
- > 1 TFLOP DP peak
- 1.5 MB L2 Cache
- 384-bit GDDR5
- PCI Express Gen3
- **3:1 SP:DP performance**

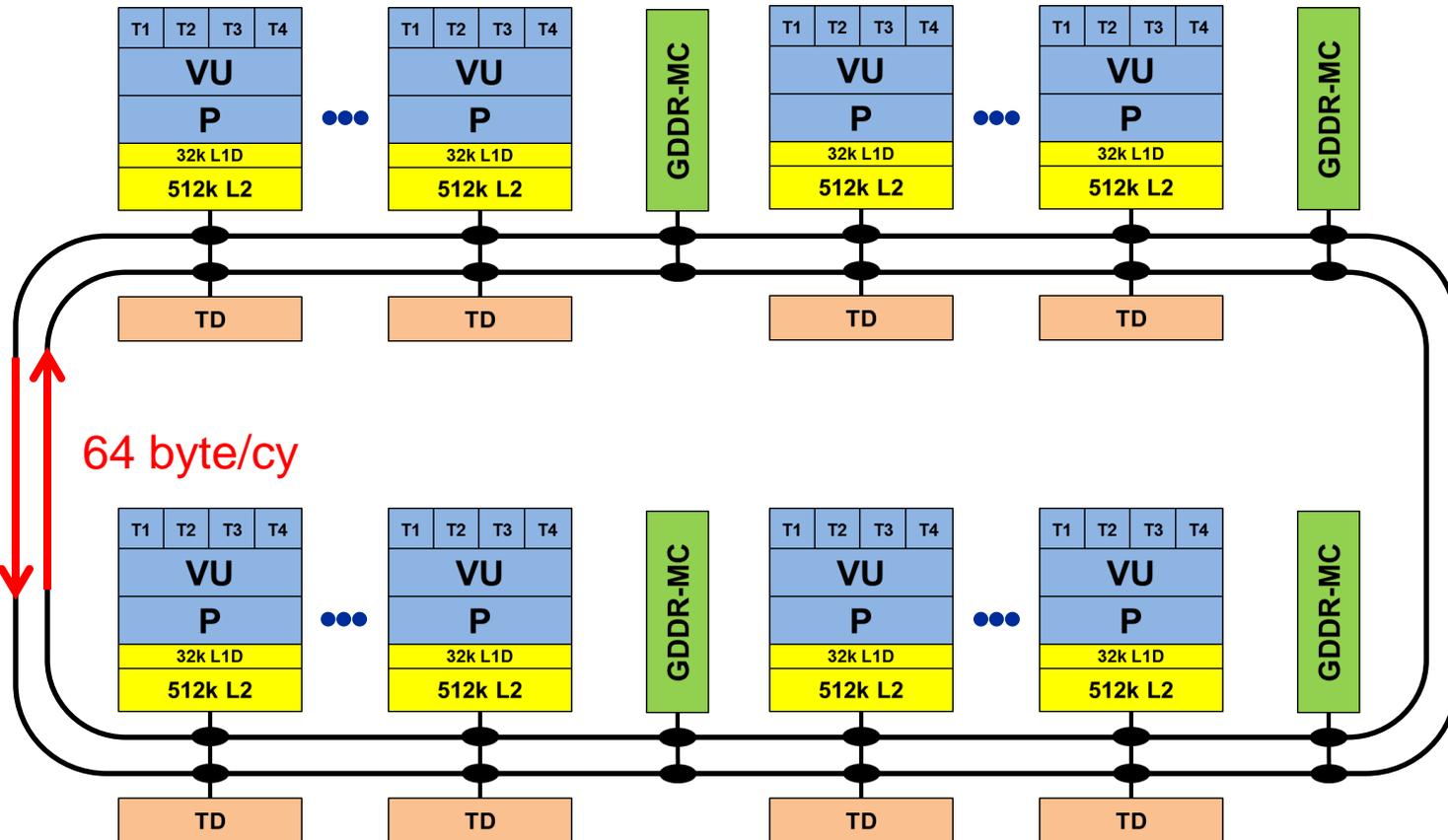


© NVIDIA Corp. Used with permission.



## Architecture

- 3B Transistors
- 60+ cores
- 512 bit SIMD
- $\approx 1$  TFLOP DP peak
- 0.5 MB L2/core
- GDDR5
- 2:1 SP:DP performance





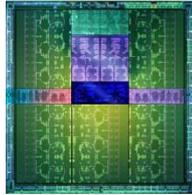
## Intel Xeon Phi

- **60+ IA32 cores** each with 512 Bit SIMD FMA unit → **480/960 SIMD DP/SP tracks**
- Clock Speed: ~1000 MHz
- Transistor count: ~3 B (22nm)
- Power consumption: ~250 W
- Peak Performance (DP): ~ 1 TF/s
- Memory BW: ~250 GB/s (GDDR5)
- Threads to execute: 60-240+
- Programming:  
Fortran/C/C++ +OpenMP + SIMD



## NVIDIA Kepler K20

- 15 SMX units each with 192 “cores” → **960/2880 DP/SP “cores”**
- Clock Speed: ~700 MHz
- Transistor count: 7.1 B (28nm)
- Power consumption: ~250 W
- Peak Performance (DP): ~ 1.3 TF/s
- Memory BW: ~ 250 GB/s (GDDR5)
- Threads to execute: 10,000+
- Programming:  
CUDA, OpenCL, (OpenACC)



- Top7: “Stampede” at Texas Center for Advanced Computing

**TOP500  
rankings  
Nov 2012**

- Top1: “Titan” at Oak Ridge National Laboratory

# Trading single thread performance for parallelism:

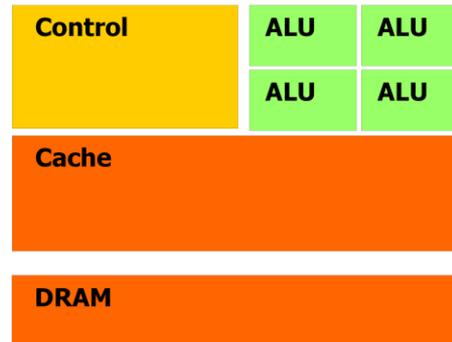
## GPGPUs vs. CPUs



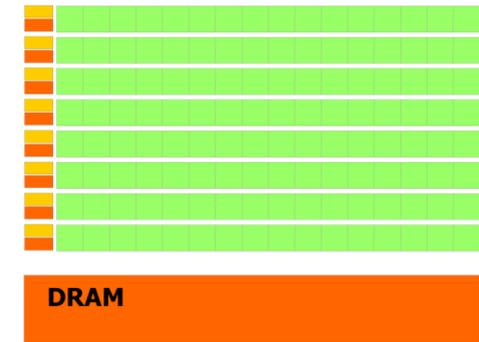
### GPU vs. CPU

light speed estimate:

1. **Compute bound:** 2-10x
2. **Memory Bandwidth:** 1-5x



CPU



GPU

	Intel Core i5 – 2500 ("Sandy Bridge")	Intel Xeon E5-2680 DP node ("Sandy Bridge")	NVIDIA K20x ("Kepler")
Cores@Clock	4 @ 3.3 GHz	2 x 8 @ 2.7 GHz	2880 @ 0.7 GHz
Performance <sup>+</sup> /core	52.8 GFlop/s	43.2 GFlop/s	1.4 GFlop/s
Threads@STREAM	<4	<16	>8000?
Total performance <sup>+</sup>	210 GFlop/s	691 GFlop/s	4,000 GFlop/s
Stream BW	18 GB/s	2 x 40 GB/s	168 GB/s (ECC=1)
Transistors / TDP	1 Billion* / 95 W	2 x (2.27 Billion/130W)	<b>7.1 Billion/250W</b>

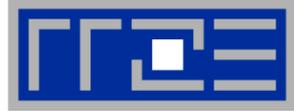
<sup>+</sup> Single Precision

\* Includes on-chip GPU and PCI-Express

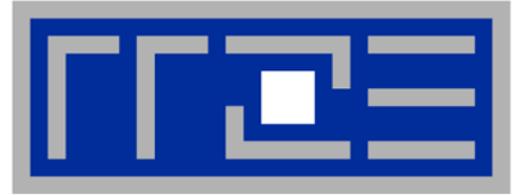
Complete compute device



- **Modern computer architecture has a rich “topology”**
- **Node-level hardware parallelism takes many forms**
  - Sockets/devices – CPU: 1-8, GPGPU: 1-6
  - Cores – moderate (CPU: 4-16) to massive (GPGPU: 1000’s)
  - SIMD – moderate (CPU: 2-8) to massive (GPGPU: 10’s-100’s)
  - Superscalarity (CPU: 2-6)
- **Exploiting performance: parallelism + bottleneck awareness**
  - **“High Performance Computing” == computing at a bottleneck**
- **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



- Preliminaries
- Introduction to multicore architecture
  - Cores, caches, chips, sockets, ccNUMA, SIMD
- **LIKWID tools**
- Microbenchmarking for architectural exploration
  - Streaming benchmarks: throughput mode
  - Streaming benchmarks: work sharing
  - Roadblocks for scalability: Saturation effects and OpenMP overhead
- Node-level performance modeling
  - The Roofline Model
  - Case study: 3D Jacobi solver and model-guided optimization
- Optimal resource utilization
  - SIMD parallelism
  - ccNUMA



## **Multicore Performance and Tools**

### **Probing node topology**

- **Standard tools**
- **likwid-topology**

# How do we figure out the node topology?



## ■ **Topology** =

- Where in the machine does core #n reside? And do I have to remember this awkward numbering anyway?
- Which cores share which cache levels?
- Which hardware threads (“logical cores”) share a physical core?

## ■ **Linux**

- `cat /proc/cpuinfo` is of limited use
- Core numbers may change across kernels and BIOSes even on identical hardware

- `numactl --hardware` prints ccNUMA node information



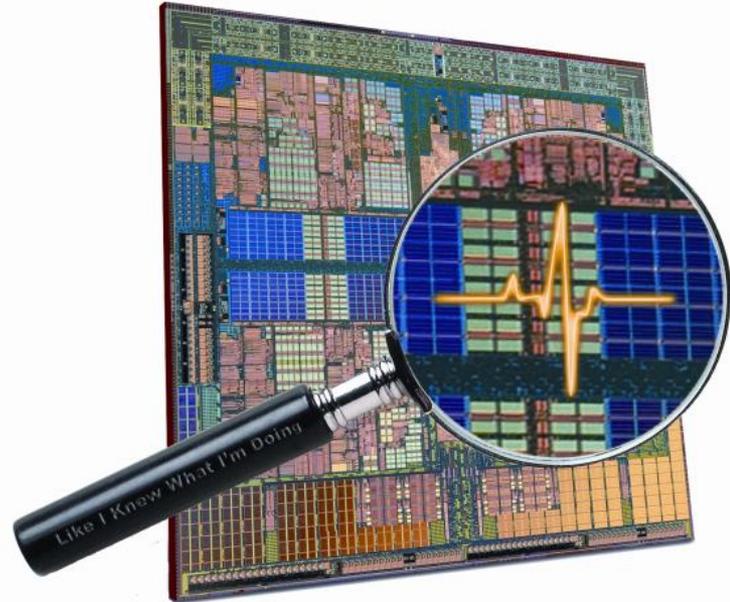
```
$ numactl --hardware
available: 4 nodes (0-3)
node 0 cpus: 0 1 2 3 4 5
node 0 size: 8189 MB
node 0 free: 3824 MB
node 1 cpus: 6 7 8 9 10 11
node 1 size: 8192 MB
node 1 free: 28 MB
node 2 cpus: 18 19 20 21 22 23
node 2 size: 8192 MB
node 2 free: 8036 MB
node 3 cpus: 12 13 14 15 16 17
node 3 size: 8192 MB
node 3 free: 7840 MB
```

- **LIKWID** tool suite:

**L**ike  
**I**  
**K**new  
**W**hat  
**I**'m  
**D**oing

- Open source tool collection  
(developed at RRZE):

<http://code.google.com/p/likwid>



J. Treibig, G. Hager, G. Wellein: *LIKWID: A lightweight performance-oriented tool suite for x86 multicore environments*. PSTI2010, Sep 13-16, 2010, San Diego, CA  
DOI: [10.1109/ICPPW.2010.38](https://doi.org/10.1109/ICPPW.2010.38)  
Preprint: <http://arxiv.org/abs/1004.4431>

- **Command line tools for Linux:**

- easy to install
- works with standard linux 2.6 kernel
- simple and clear to use
- supports Intel and AMD CPUs



- **Current tools:**

- **likwid-topology**: Print thread and cache topology
- **likwid-pin**: Pin threaded application without touching code
- **likwid-perfctr**: Measure performance counters
- **likwid-mpirun**: mpirun wrapper script for easy LIKWID integration
- **likwid-bench**: Low-level bandwidth benchmark generator tool
- ... some more

# Output of `likwid-topology -g`

on one node of Cray XE6 "Hermit"



-----  
CPU type: AMD Interlagos processor

\*\*\*\*\*

## Hardware Thread Topology

\*\*\*\*\*

Sockets: 2  
Cores per socket: 16  
Threads per core: 1

-----

HWTThread	Thread	Core	Socket
0	0	0	0
1	0	1	0
2	0	2	0
3	0	3	0
[...]			
16	0	0	1
17	0	1	1
18	0	2	1
19	0	3	1
[...]			

-----  
Socket 0: ( 0 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 )

Socket 1: ( 16 17 18 19 20 21 22 23 24 25 26 27 28 29 30 31 )  
-----

## Cache Topology

\*\*\*\*\*

Level: 1

Size: 16 kB

Cache groups: ( 0 ) ( 1 ) ( 2 ) ( 3 ) ( 4 ) ( 5 ) ( 6 ) ( 7 ) ( 8 ) ( 9 ) ( 10 ) ( 11 ) ( 12 ) ( 13 )  
( 14 ) ( 15 ) ( 16 ) ( 17 ) ( 18 ) ( 19 ) ( 20 ) ( 21 ) ( 22 ) ( 23 ) ( 24 ) ( 25 ) ( 26 ) ( 27 ) ( 28 )  
( 29 ) ( 30 ) ( 31 )

# Output of likwid-topology continued



```
-----  
Level:  2  
Size:   2 MB  
Cache groups:  ( 0 1 ) ( 2 3 ) ( 4 5 ) ( 6 7 ) ( 8 9 ) ( 10 11 ) ( 12 13 ) ( 14 15 ) ( 16 17 ) ( 18  
19 ) ( 20 21 ) ( 22 23 ) ( 24 25 ) ( 26 27 ) ( 28 29 ) ( 30 31 )  
-----
```

```
Level:  3  
Size:   6 MB  
Cache groups:  ( 0 1 2 3 4 5 6 7 ) ( 8 9 10 11 12 13 14 15 ) ( 16 17 18 19 20 21 22 23 ) ( 24 25 26  
27 28 29 30 31 )  
-----
```

```
*****  
NUMA Topology  
*****  
NUMA domains: 4  
-----
```

```
Domain 0:  
Processors:  0 1 2 3 4 5 6 7  
Memory: 7837.25 MB free of total 8191.62 MB  
-----
```

```
Domain 1:  
Processors:  8 9 10 11 12 13 14 15  
Memory: 7860.02 MB free of total 8192 MB  
-----
```

```
Domain 2:  
Processors:  16 17 18 19 20 21 22 23  
Memory: 7847.39 MB free of total 8192 MB  
-----
```

```
Domain 3:  
Processors:  24 25 26 27 28 29 30 31  
Memory: 7785.02 MB free of total 8192 MB  
-----
```

# Output of likwid-topology continued



\*\*\*\*\*

Graphical:

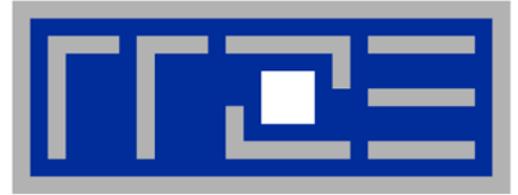
\*\*\*\*\*

Socket 0:

0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
16kB															
2MB															
6MB								6MB							

Socket 1:

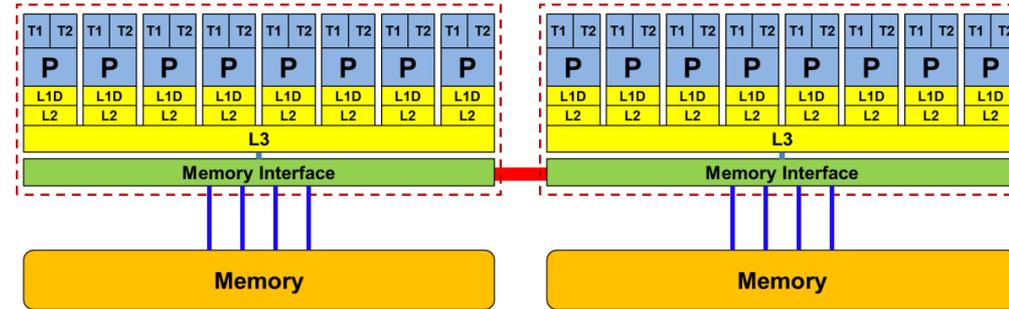
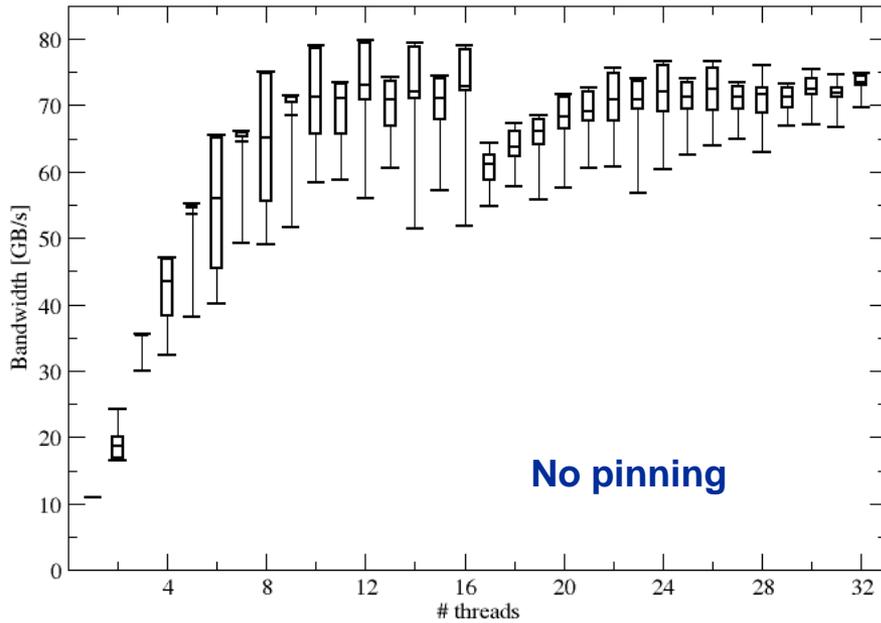
16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31
16kB															
2MB															
6MB								6MB							



## **Enforcing thread/process-core affinity under the Linux OS**

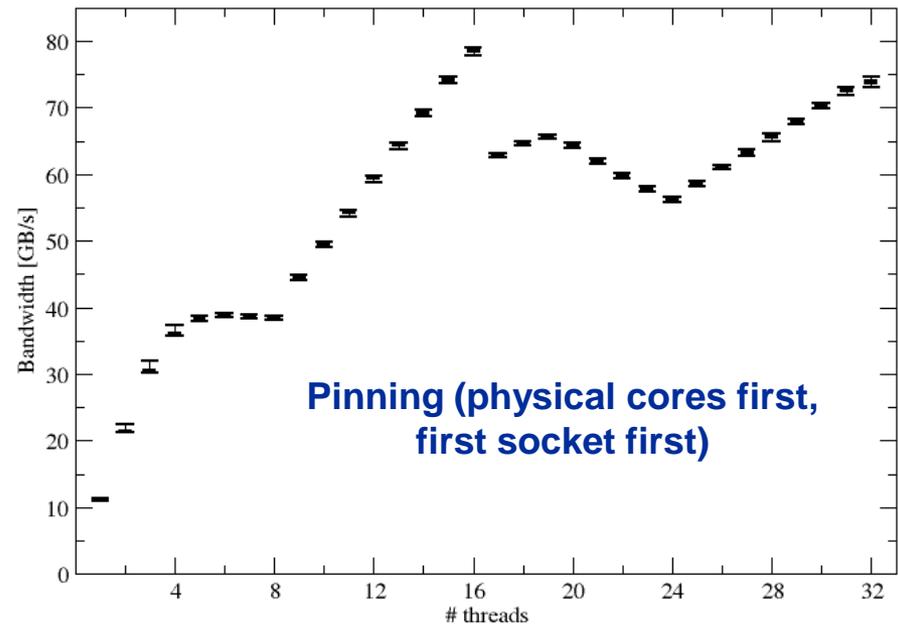
- **Standard tools and OS affinity facilities  
under program control**
- **likwid-pin**

# Example: STREAM benchmark on 16-core Sandy Bridge: Anarchy vs. thread pinning



There are several reasons for caring about affinity:

- Eliminating performance variation
- Making use of architectural features
- Avoiding resource contention





- `taskset [OPTIONS] [MASK | -c LIST ] \  
[PID | command [args]...]`
- **taskset** restricts processes/threads to a set of CPUs. Examples:  
  

```
taskset 0x0006 ./a.out  
taskset -c 4 33187
```
- **Processes/threads can still move within the set!**
- **Alternative: let process/thread bind itself by executing syscall**  

```
#include <sched.h>  
int sched_setaffinity(pid_t pid, unsigned int len,  
                    unsigned long *mask);
```
- **Disadvantage: which CPUs should you bind to on a non-exclusive machine?**
- **Still of value on multicore/multisocket cluster nodes, UMA or ccNUMA**



- Complementary tool: `numactl`

**Example:** `numactl --physcpubind=0,1,2,3 command [args]`

**Restricts process to specified physical core numbers**

**Example:** `numactl --cpunodebind=1 command [args]`

**Restricts process to specified ccNUMA node(s)**

- Many more options (e.g., interleave memory across nodes)
  - → see section on ccNUMA optimization
- Diagnostic command (see earlier):  
`numactl --hardware`
- Again, this is not suitable for a shared machine



- **Highly OS-dependent system calls**
  - But available on all systems
  - Linux: `sched_setaffinity()`, PLPA (see below) → `hwloc`
  - Windows: `SetThreadAffinityMask()`
  - ...
- **Support for “semi-automatic” pinning in some compilers/environments**
  - Intel compilers > V9.1 (`KMP_AFFINITY` environment variable)
  - PGI, Pathscale, GNU
  - SGI Altix `dp1ace` (works with logical CPU numbers!)
  - Generic Linux: `taskset`, `numactl`, `likwid-pin` (see below)
  - **OpenMP 4.0**
- **Affinity awareness in MPI libraries**
  - OpenMPI
  - Intel MPI
  - Cray MPI
  - ...



- Pins processes and threads to specific cores **without touching code**
- Directly supports pthreads, gcc OpenMP, Intel OpenMP
- Based on combination of wrapper tool together with overloaded pthread library → **binary must be dynamically linked!**
- Can also be used as a superior **replacement for taskset**
- Supports **logical core numbering** within a node and within an existing CPU set
  - Useful for running inside CPU sets defined by someone else, e.g., the MPI start mechanism or a batch system
- **Usage examples:**
  - Physical numbering (as given by likwid-topology):  
`likwid-pin -c 0,2,4-6 ./myApp parameters`
  - Logical numbering by topological entities:  
`likwid-pin -c S0:0-3 ./myApp parameters`



- Running the STREAM benchmark with likwid-pin:

```
$ export OMP_NUM_THREADS=4
$ likwid-pin -c 0,1,4,5 ./stream
[likwid-pin] Main PID -> core 0 - OK
-----
Double precision appears to have 16 digits of accuracy
Assuming 8 bytes per DOUBLE PRECISION word
-----
[... some STREAM output omitted ...]
The *best* time for each test is used
*EXCLUDING* the first and last iterations
[pthread wrapper] PIN_MASK: 0->1 1->4 2->5
[pthread wrapper] SKIP MASK: 0x1
[pthread wrapper 0] Notice: Using libpthread.so.0
    threadid 1073809728 -> SKIP
[pthread wrapper 1] Notice: Using libpthread.so.0
    threadid 1078008128 -> core 1 - OK
[pthread wrapper 2] Notice: Using libpthread.so.0
    threadid 1082206528 -> core 4 - OK
[pthread wrapper 3] Notice: Using libpthread.so.0
    threadid 1086404928 -> core 5 - OK
[... rest of STREAM output omitted ...]
```

Main PID always pinned

Skip shepherd thread

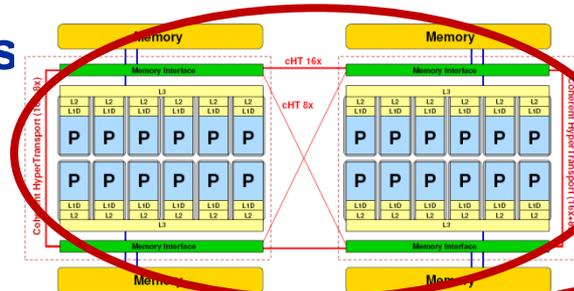
Pin all spawned threads in turn





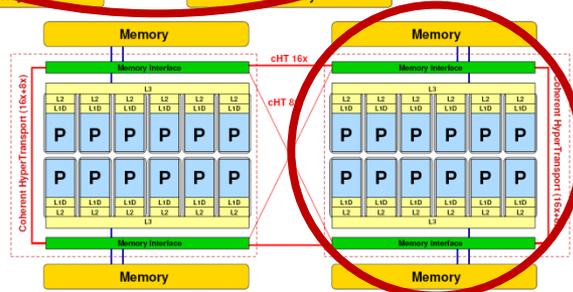
- Possible unit prefixes

**N** node

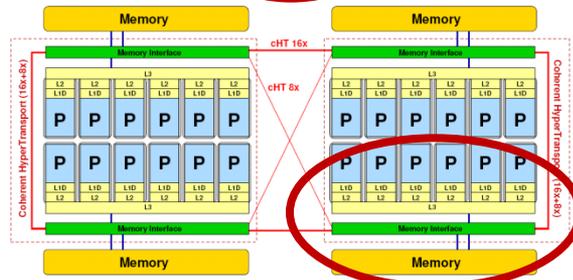


Default if -c is not specified!

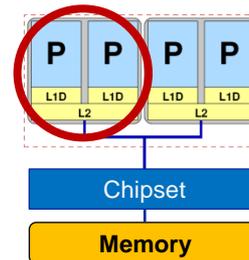
**S** socket



**M** NUMA domain



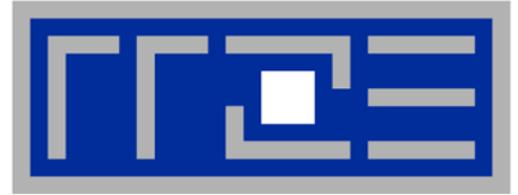
**C** outer level cache group



# DEMO



- Preliminaries
- Introduction to multicore architecture
  - Cores, caches, chips, sockets, ccNUMA, SIMD
- LIKWID tools
- **Microbenchmarking for architectural exploration**
  - Streaming benchmarks: throughput mode
  - Streaming benchmarks: work sharing
  - Roadblocks for scalability: Saturation effects and OpenMP overhead
- **Node-level performance modeling**
  - The Roofline Model
  - Case study: 3D Jacobi solver and model-guided optimization
- **Optimal resource utilization**
  - SIMD parallelism
  - ccNUMA



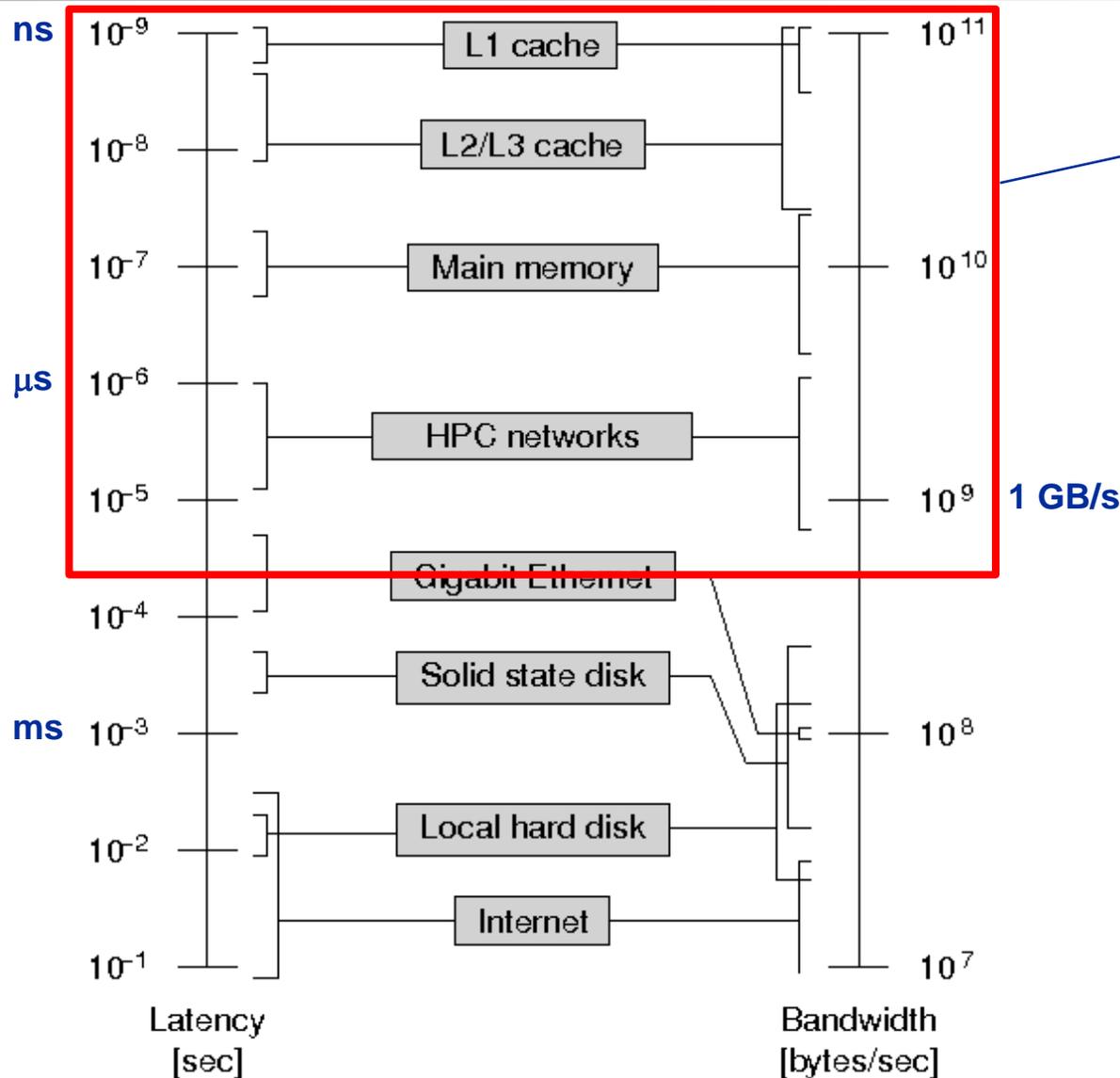
# **Microbenchmarking for architectural exploration**

**Probing of the memory hierarchy**

**Saturation effects in cache and memory**

**Typical OpenMP overheads**

# Latency and bandwidth in modern computer environments



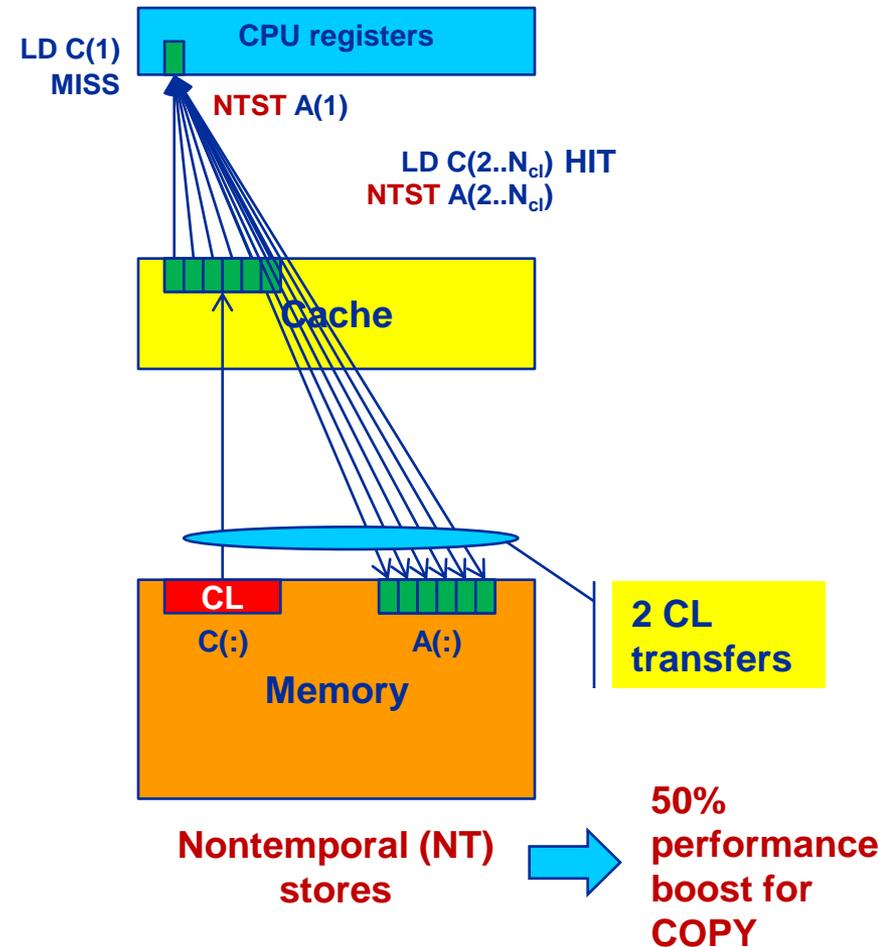
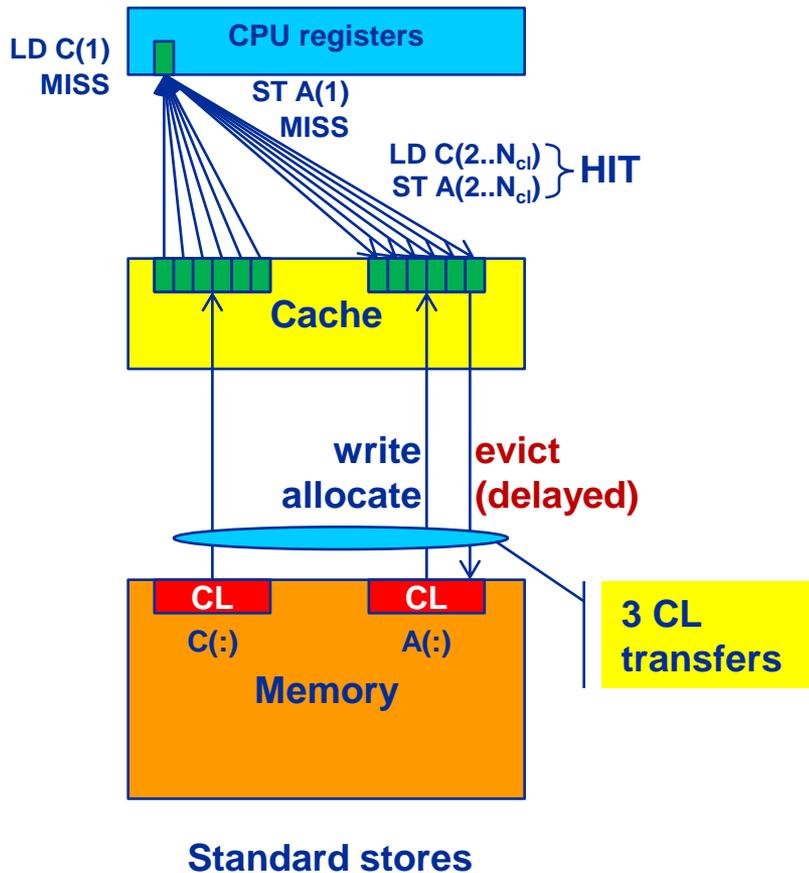
HPC plays here

**Avoiding slow data paths is the key to most performance optimizations!**

# Recap: Data transfers in a memory hierarchy



- How does data travel from memory to the CPU and back?
- Example: Array copy  $A(:) = C(:)$





## Simple streaming benchmark:

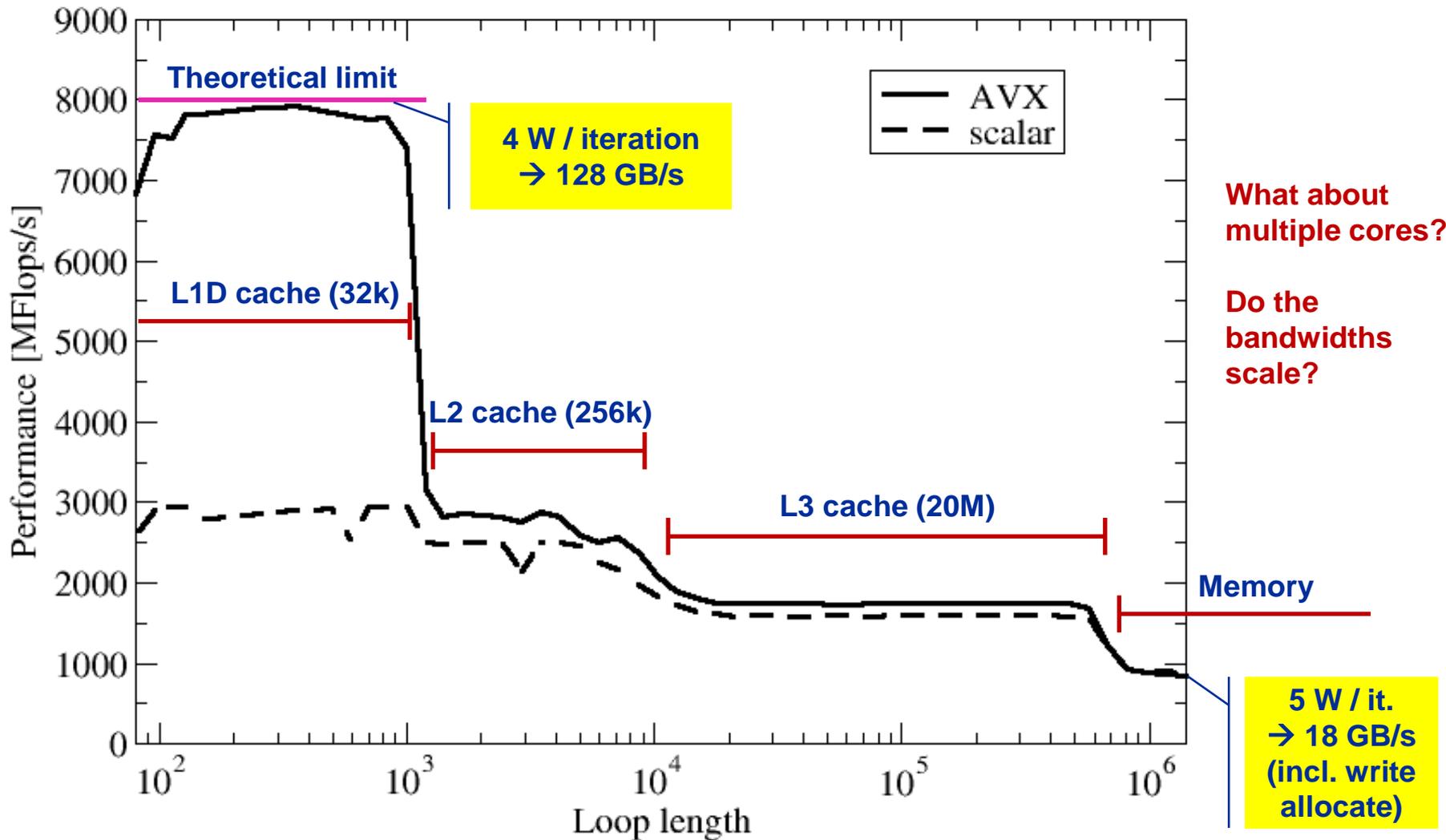
```
double precision, dimension(N) :: A,B,C,D
A=1.d0; B=A; C=A; D=A
```

```
do j=1,NITER
  do i=1,N
    A(i) = B(i) + C(i) * D(i)
  enddo
  if(.something.that.is.never.true.) then
    call dummy(A,B,C,D)
  endif
enddo
```

Prevents smarty-pants  
compilers from doing  
“clever” stuff

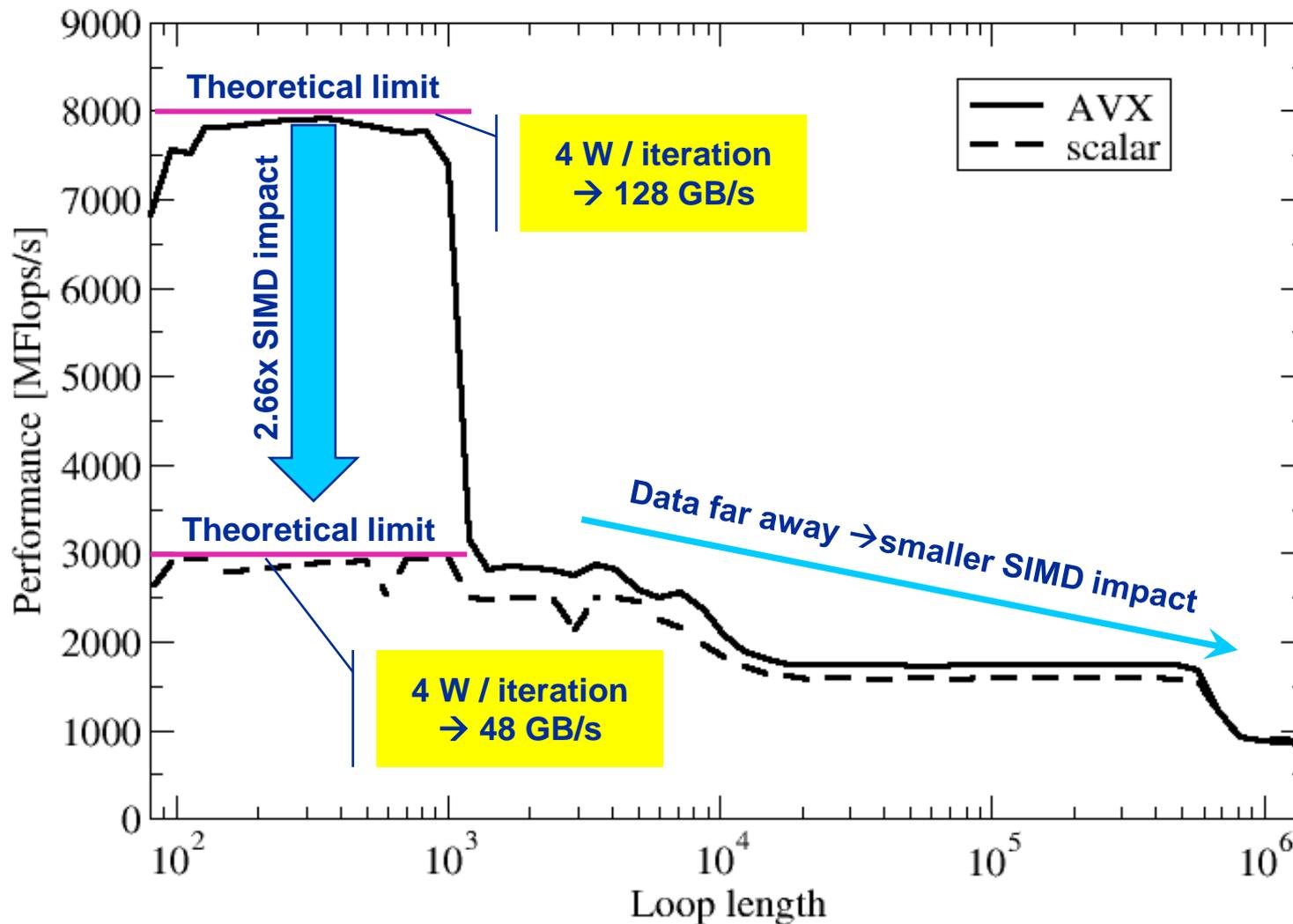
- Report performance for different N
- Choose NITER so that accurate time measurement is possible
- **This kernel is limited by data transfer performance for all memory levels on all current architectures!**

# A (:) = B (:) + C (:) \* D (:) on one Sandy Bridge core (3 GHz)



What about multiple cores?

Do the bandwidths scale?



See later for more on SIMD benefits



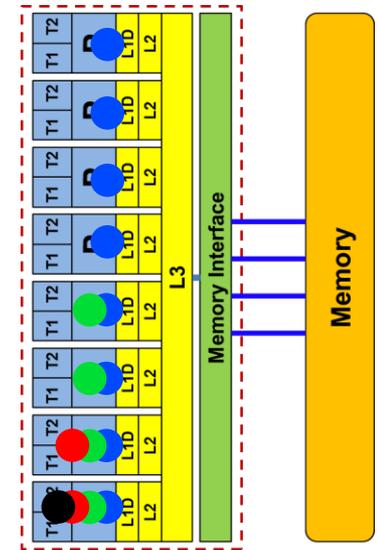
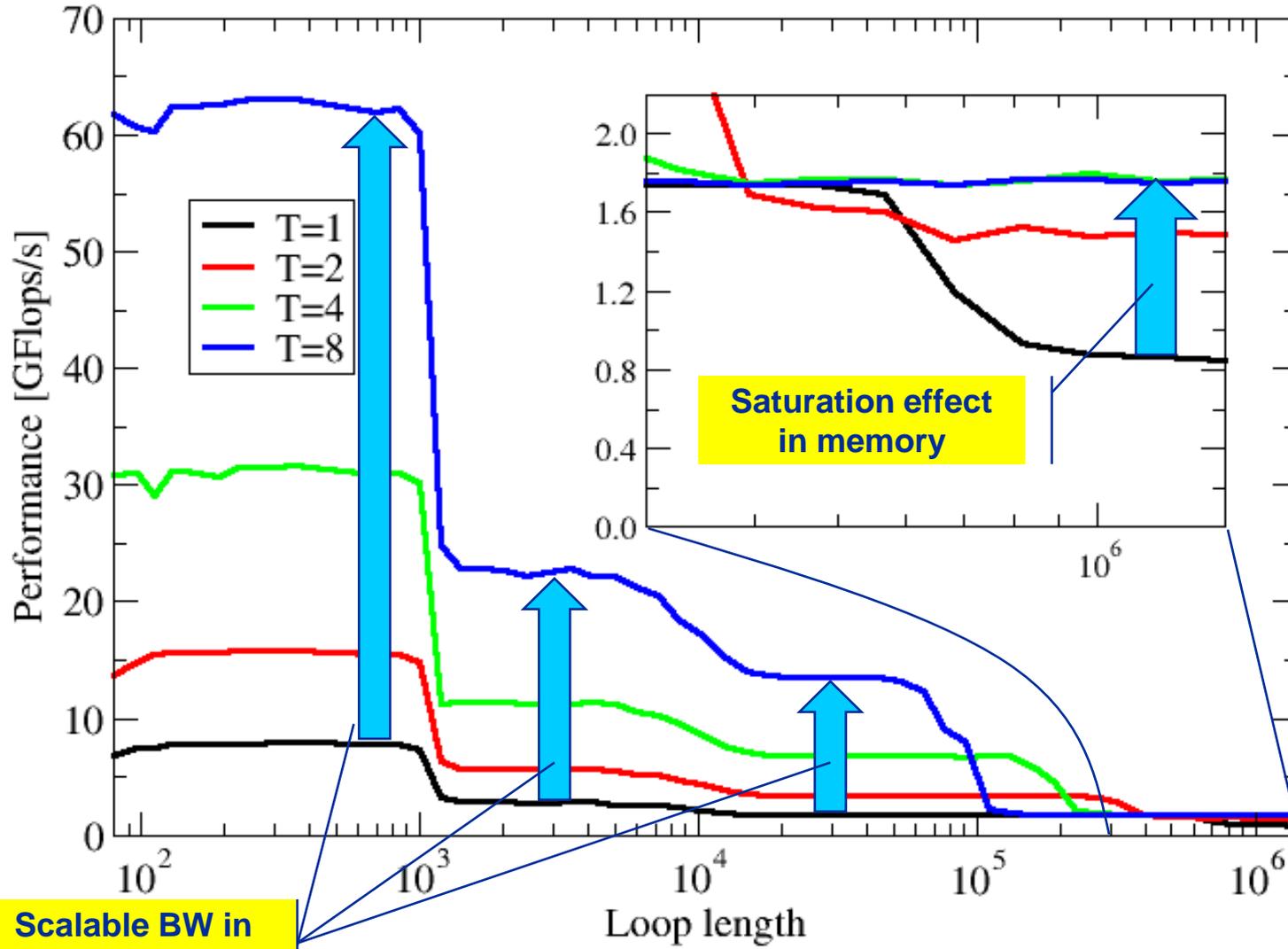
Every core runs its own, independent triad benchmark

```
double precision, dimension(:), allocatable :: A,B,C,D

!$OMP PARALLEL private(i,j,A,B,C,D)
allocate(A(1:N),B(1:N),C(1:N),D(1:N))
A=1.d0; B=A; C=A; D=A
do j=1,NITER
  do i=1,N
    A(i) = B(i) + C(i) * D(i)
  enddo
  if(.something.that.is.never.true.) then
    call dummy(A,B,C,D)
  endif
enddo
!$OMP END PARALLEL
```

→ pure hardware probing, no impact from OpenMP overhead

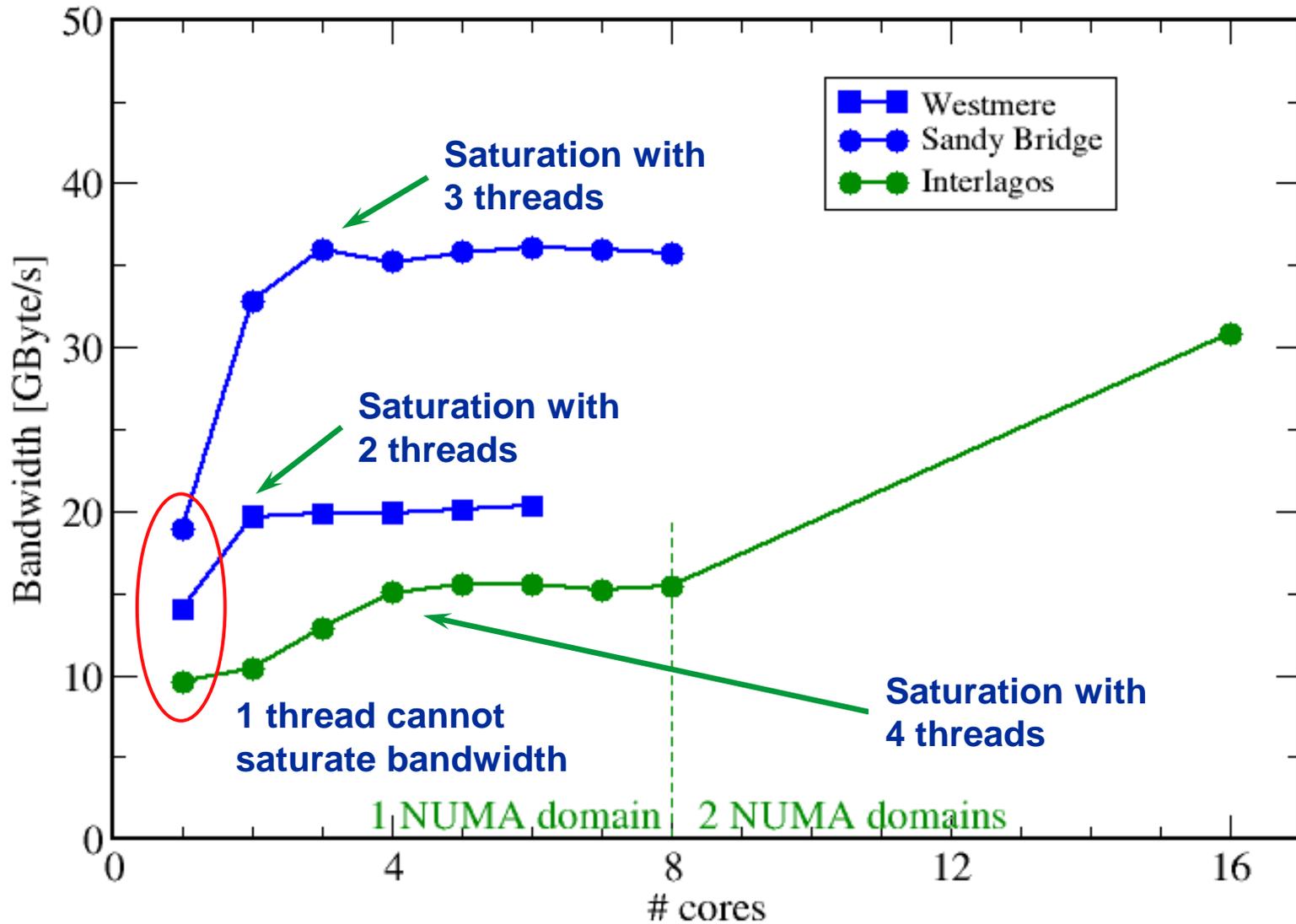
# Throughput vector triad on Sandy Bridge socket (3 GHz)



Scalable BW in L1, L2, L3 cache

# Bandwidth limitations: Main Memory

Scalability of shared data paths *inside a NUMA domain* (V-Triad)





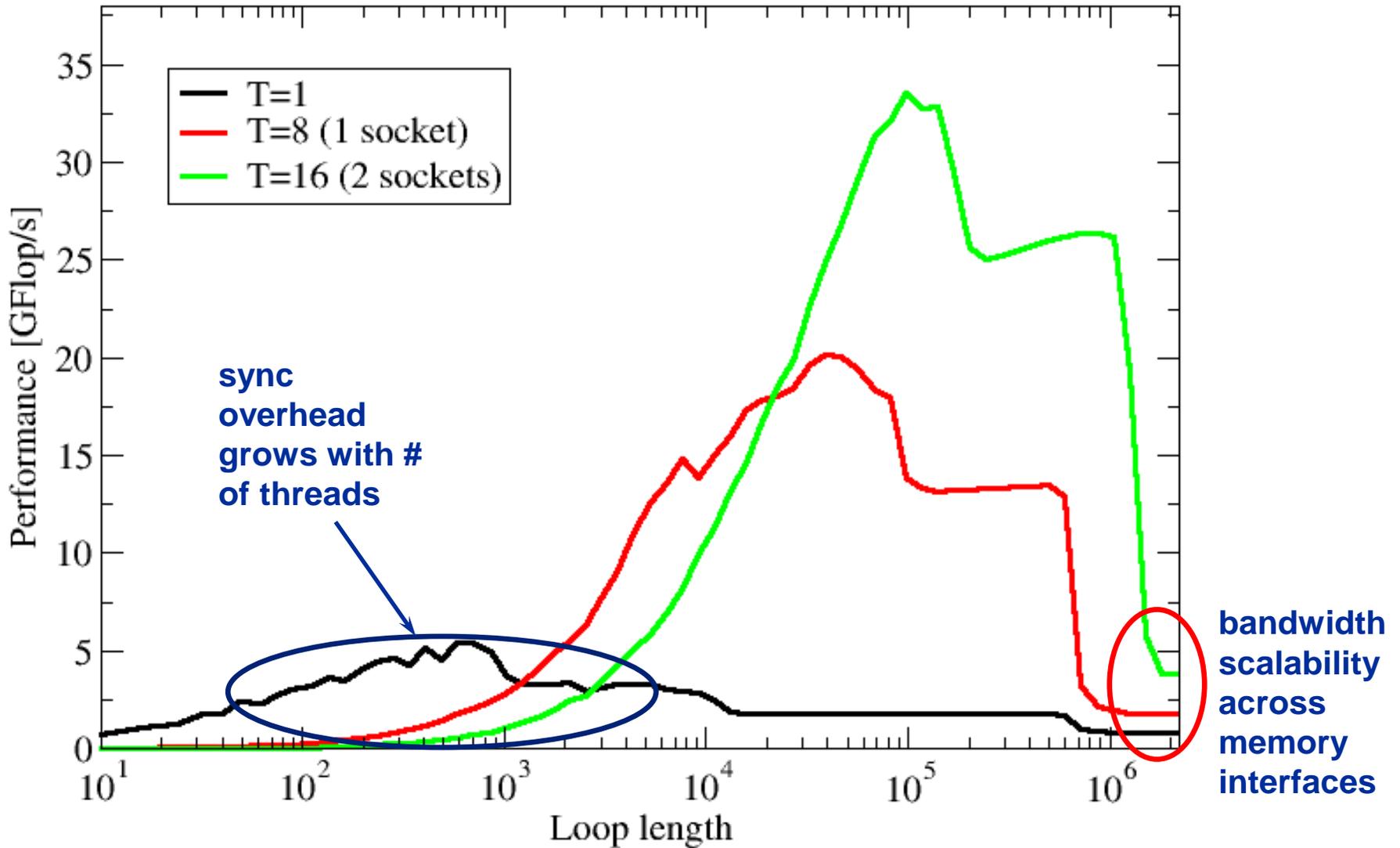
## OpenMP work sharing in the benchmark loop

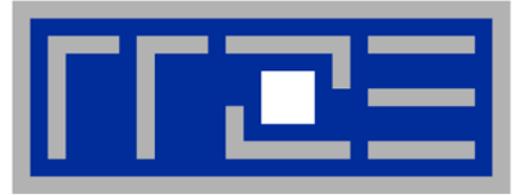
```
double precision, dimension(:), allocatable :: A,B,C,D

allocate(A(1:N),B(1:N),C(1:N),D(1:N))
A=1.d0; B=A; C=A; D=A
!$OMP PARALLEL private(i,j)
do j=1,NITER
!$OMP DO
  do i=1,N
    A(i) = B(i) + C(i) * D(i)
  enddo
!$OMP END DO
  if(.something.that.is.never.true.) then
    call dummy(A,B,C,D)
  endif
enddo
!$OMP END PARALLEL
```

Implicit barrier

# OpenMP vector triad on Sandy Bridge socket (3 GHz)





# **OpenMP performance issues on multicore**

**Synchronization (barrier) overhead**

# Welcome to the multi-/many-core era

*Synchronization of threads may be expensive!*



!\$OMP PARALLEL ...

...

!\$OMP BARRIER

!\$OMP DO

...

!\$OMP ENDDO

!\$OMP END PARALLEL

Threads are synchronized at **explicit** AND **implicit** barriers. These are a main source of overhead in OpenMP programs.

Determine costs via modified OpenMP  
Microbenchmarks testcase (epcc)

## On x86 systems there is no hardware support for synchronization!

- Next slide: Test **OpenMP** Barrier performance...
- for different compilers
- and different topologies:
  - shared cache
  - shared socket
  - between sockets
- and different thread counts
  - 2 threads
  - full domain (chip, socket, node)

# Thread synchronization overhead on SandyBridge-EP

Barrier overhead in CPU cycles



2 Threads	Intel 13.1.0	GCC 4.7.0	GCC 4.6.1
Shared L3	384	5242	4616
SMT threads	2509	3726	3399
Other socket	1375	5959	4909

 Gcc still not very competitive

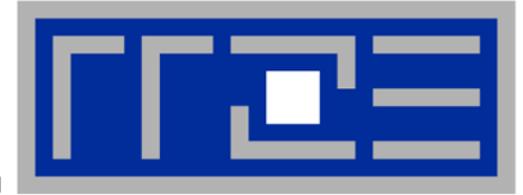
Intel compiler 

Full domain	Intel 13.1.0	GCC 4.7.0	GCC 4.6.1
Socket	1497	14546	14418
Node	3401	34667	29788
Node +SMT	6881	59038	58898

**Xeon Phi (240 threads):  
18500**



- **Affinity matters!**
  - Almost all performance properties depend on the position of
    - Data
    - Threads/processes
  - Consequences
    - Know where your threads are running
    - Know where your data is
  
- **Bandwidth bottlenecks are ubiquitous**
  
- **Synchronization overhead may be an issue**
  - ... and also depends on affinity!
  - Many-core poses new challenges in terms of synchronization



**Case study:  
OpenMP-parallel sparse matrix-vector  
multiplication (part 1)**

**A simple (but sometimes not-so-simple)  
example for bandwidth-bound code and  
saturation effects in memory**



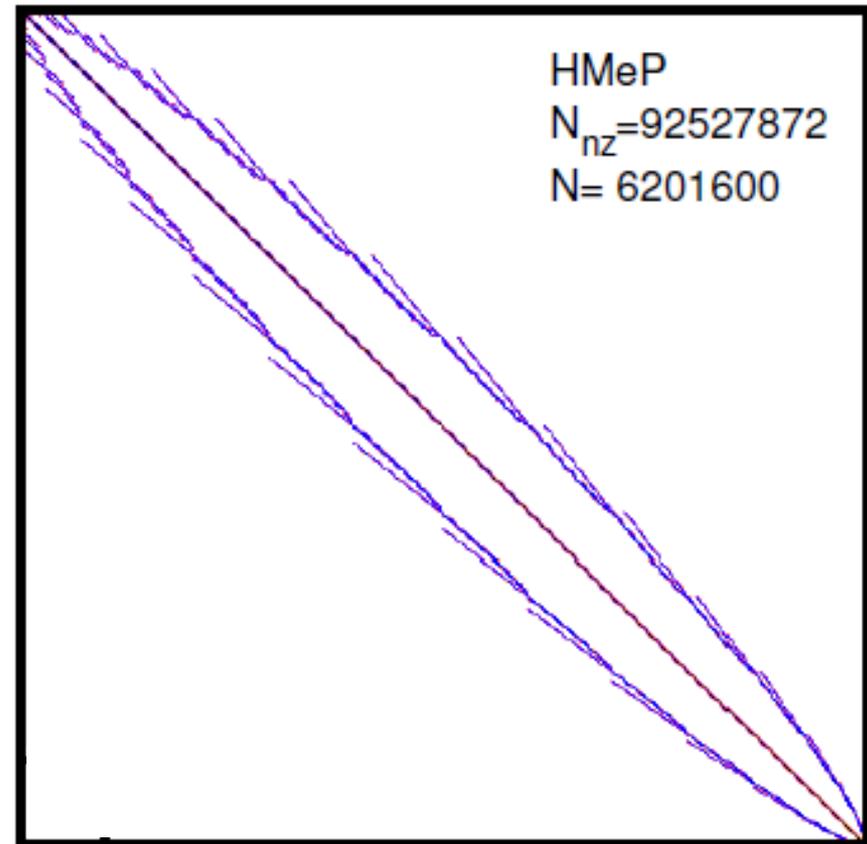
- Important kernel in many applications (matrix diagonalization, solving linear systems)
- **Strongly memory-bound for large data sets**
  - Streaming, with partially indirect access:

```
!$OMP parallel do
do i = 1, Nr
  do j = row_ptr(i), row_ptr(i+1) - 1
    c(i) = c(i) + val(j) * b(col_idx(j))
  enddo
enddo
!$OMP end parallel do
```

- Usually many spMVMs required to solve a problem
- **Following slides: Performance data on one 24-core AMD Magny Cours node**

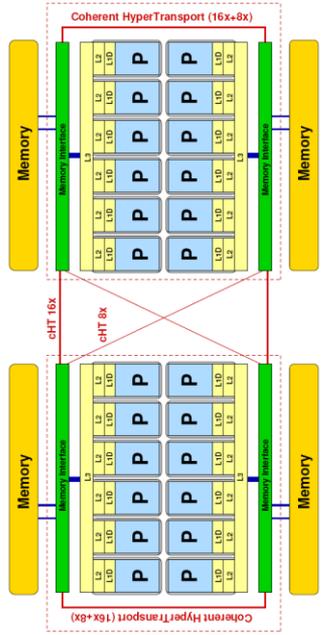


- **Data storage format is crucial for performance properties**
  - Most useful general format: Compressed Row Storage (**CRS**)
  - SpMVM is **easily parallelizable** in shared and distributed memory
  
- **For large problems, spMVM is inevitably memory-bound**
  - **Intra-LD saturation effect** on modern multicores
  
- **MPI-parallel spMVM is often communication-bound**
  - See later part for what we can do about this...

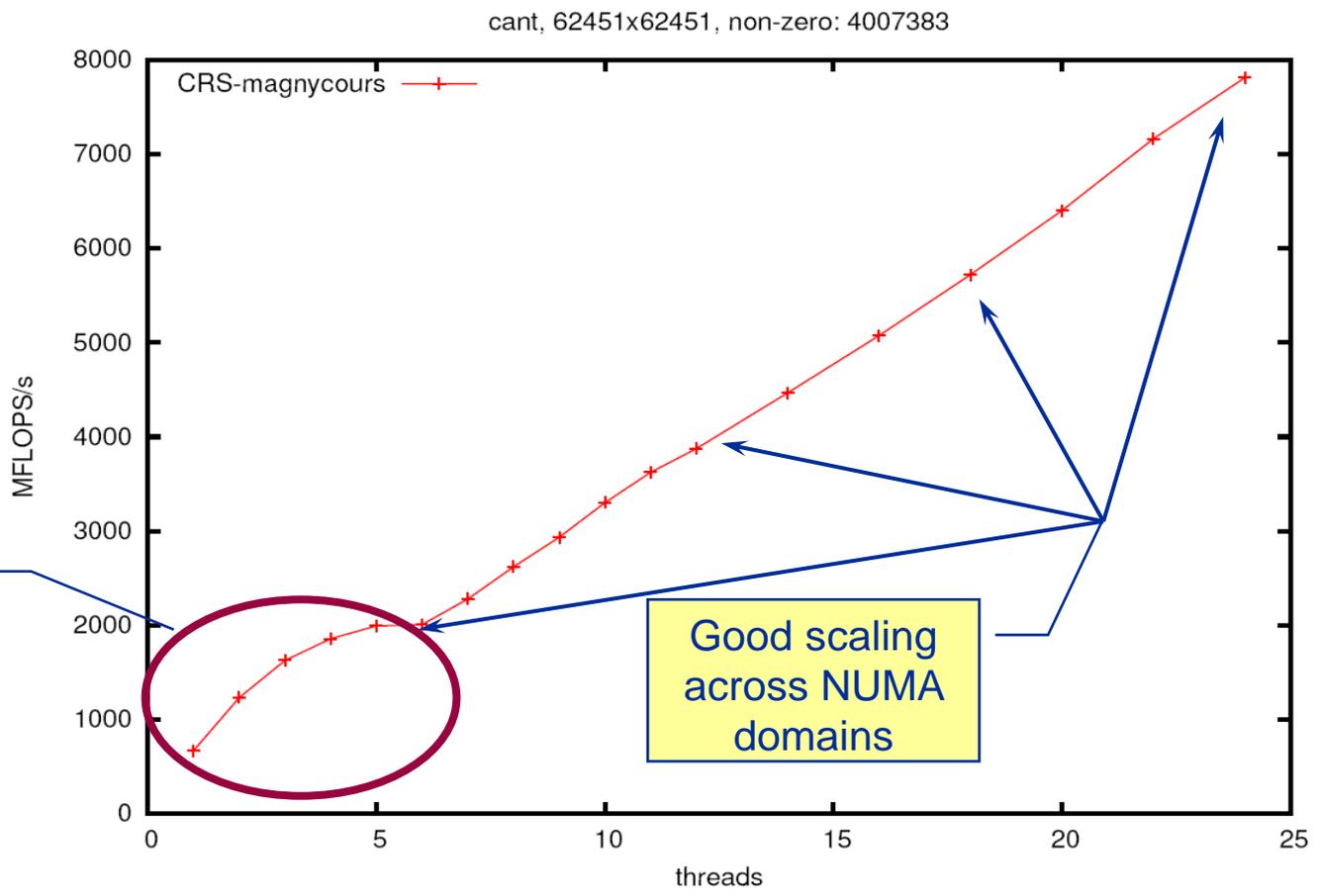




### Case 1: Large matrix



Intrasocket bandwidth bottleneck

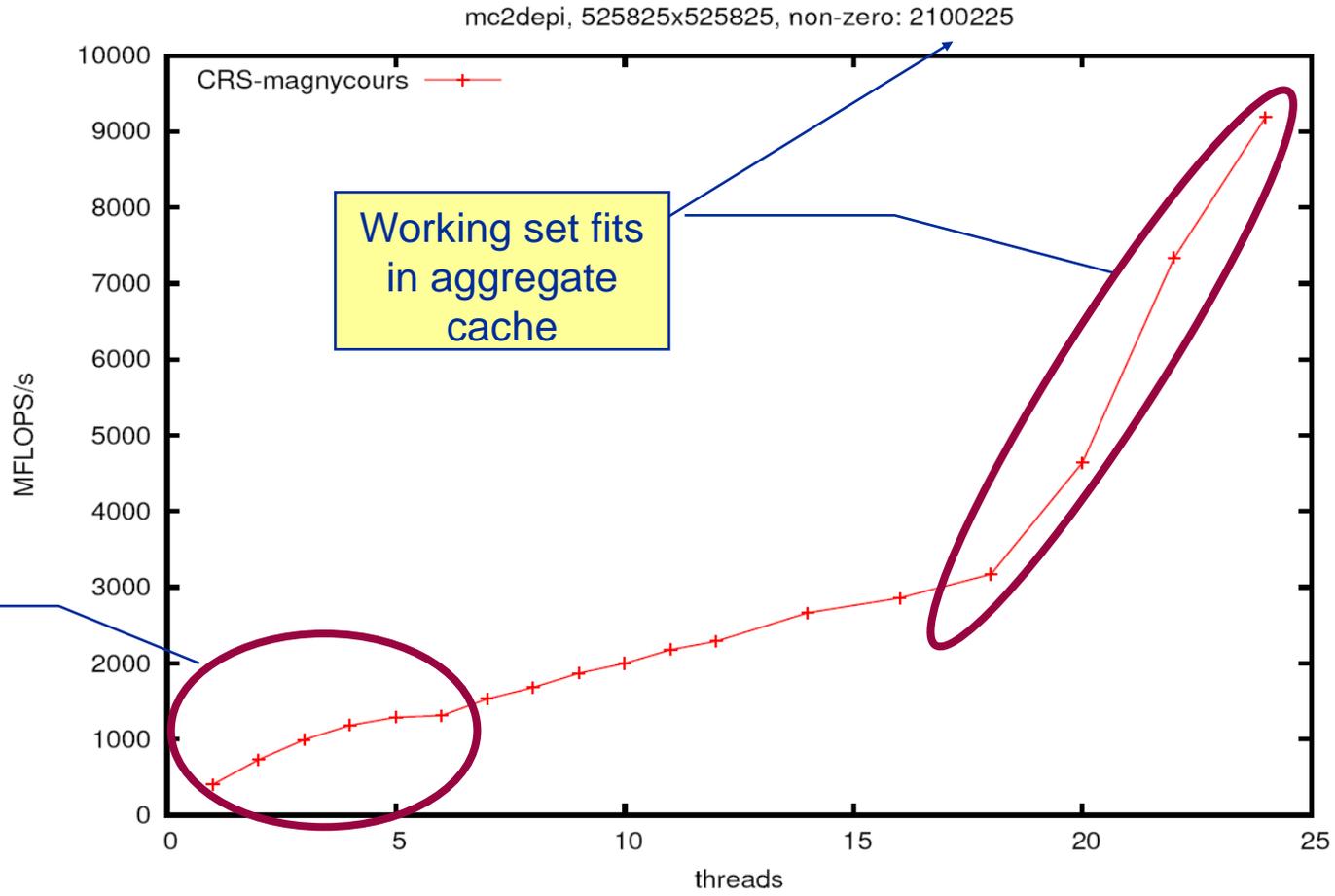




### Case 2: Medium size



Intrsocket bandwidth bottleneck

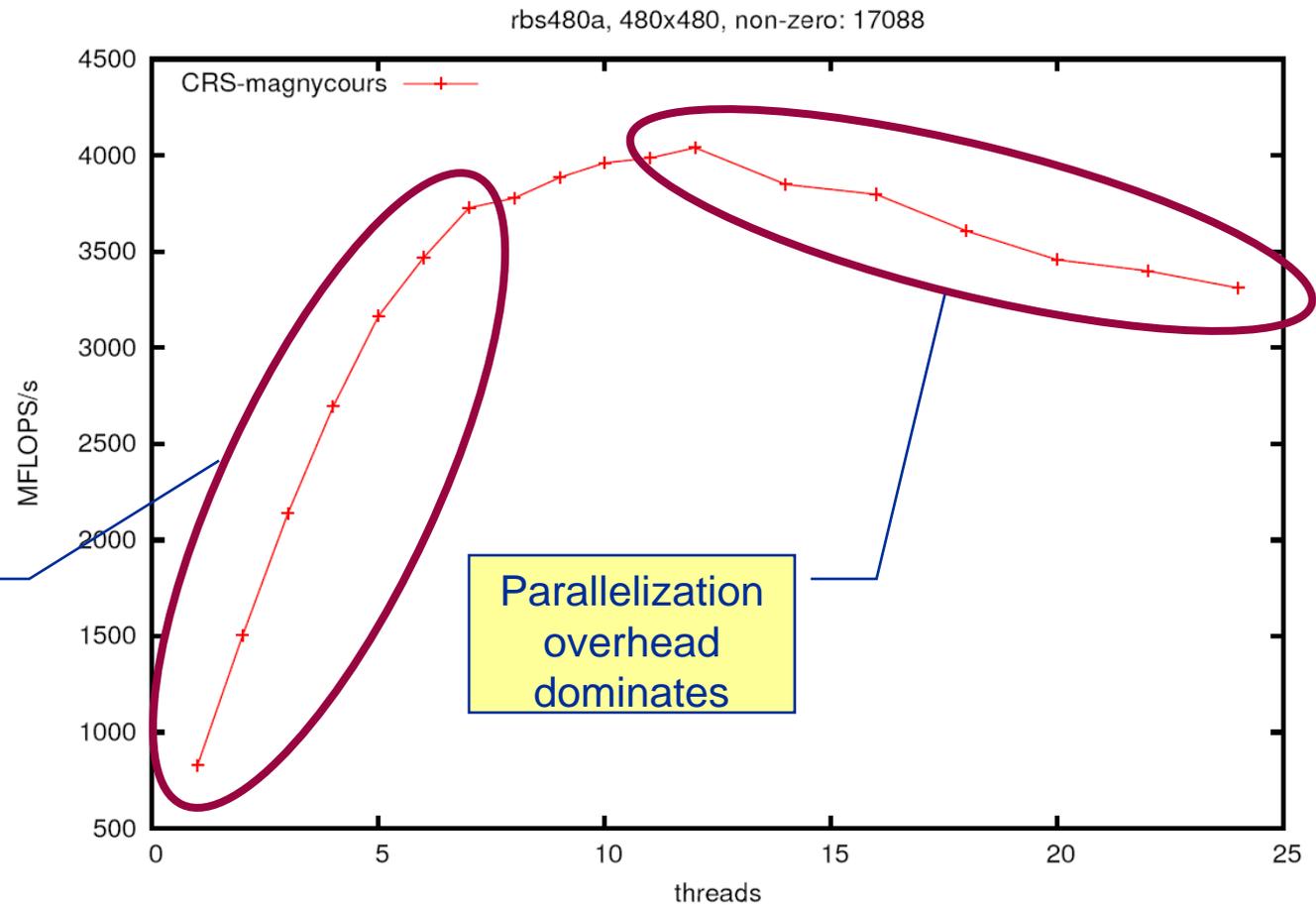




### Case 3: Small size



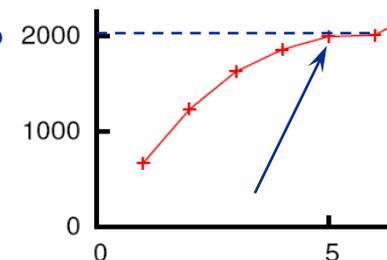
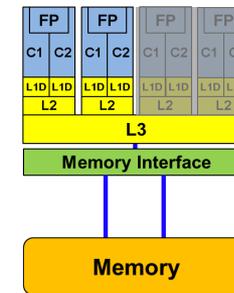
No bandwidth bottleneck



Parallelization overhead dominates

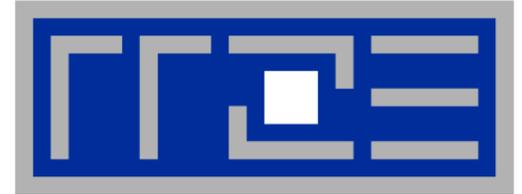


- If the problem is “large”, bandwidth saturation on the socket is a reality
  - → There are “**spare cores**”
  - Very **common performance pattern**
- **What to do with spare cores?**
  - Let them **idle** → **saves energy** with minor loss in time to solution
  - Use them for other tasks, such as **MPI communication**
- Can we **predict the saturated performance?**
  - Bandwidth-based performance **modeling!**
  - What is the significance of the **indirect access?**  
Can it be modeled?
- Can we predict the **saturation point?**
  - ... and why is this important?





- Preliminaries
- Introduction to multicore architecture
  - Cores, caches, chips, sockets, ccNUMA, SIMD
- LIKWID tools
- Microbenchmarking for architectural exploration
  - Streaming benchmarks: throughput mode
  - Streaming benchmarks: work sharing
  - Roadblocks for scalability: Saturation effects and OpenMP overhead
- **Node-level performance modeling**
  - The Roofline Model
  - Case study: 3D Jacobi solver and model-guided optimization
- Optimal resource utilization
  - SIMD parallelism
  - ccNUMA



## **“Simple” performance modeling: The Roofline Model**

**Loop-based performance modeling: Execution vs. data transfer**

**Example: array summation**

**Example: A 3D Jacobi solver**

**Model-guided optimization**



1.  $P_{\max}$  = **Applicable peak performance** of a loop, assuming that data comes from L1 cache (this is not necessarily  $P_{\text{peak}}$ )
2.  $I$  = **Computational intensity** (“work” per byte transferred) over the slowest data path utilized (“the bottleneck”)
  - Code balance  $B_C = I^{-1}$
3.  $b_S$  = **Applicable peak bandwidth** of the slowest data path utilized

Expected performance:

$$P = \min(P_{\max}, I \cdot b_S)$$

<sup>1</sup> W. Schönauer: Scientific Supercomputing: Architecture and Use of Shared and Distributed Memory Parallel Computers. (2000)

<sup>2</sup> S. Williams: Auto-tuning Performance on Multicore Computers. UCB Technical Report No. UCB/EECS-2008-164. PhD thesis (2008)



**Example: Vector triad  $A(:) = B(:) + C(:) * D(:)$   
on a 2.7 GHz 8-core Sandy Bridge chip (AVX vectorized)**

- $b_S = 40 \text{ GB/s}$
  - $B_c = (4+1) \text{ Words} / 2 \text{ Flops} = 2.5 \text{ W/F}$  (including write allocate)  
→  $I = 0.4 \text{ F/W} = 0.05 \text{ F/B}$
- $I \cdot b_S = 2.0 \text{ GF/s}$  (1.2 % of peak performance)
- $P_{\text{peak}} = 173 \text{ Gflop/s}$  (8 FP units x (4+4) Flops/cy x 2.7 GHz)
  - $P_{\text{max}}?$  → Observe LD/ST throughput maximum of 1 AVX Load and ½ AVX store per cycle → 3 cy / 8 Flops →  $P_{\text{max}} = 57.6 \text{ Gflop/s}$  (33% peak)

$$P = \min(P_{\text{max}}, I \cdot b_S) = \min(57.6, 2.0) \text{ GFlop/s} \\ = 2.0 \text{ GFlop/s}$$



**Example: Vector triad  $A(:) = B(:) + C(:) * D(:)$   
on a 1.05 GHz 60-core Intel Xeon Phi chip (vectorized)**

- $b_S = 160 \text{ GB/s}$
- $B_c = (4+1) \text{ Words} / 2 \text{ Flops} = 2.5 \text{ W/F}$  (including write allocate)  
→  $I = 0.4 \text{ F/W} = 0.05 \text{ F/B}$
- $I \cdot b_S = 8.0 \text{ GF/s}$  (0.8 % of peak performance)
- $P_{\text{peak}} = 1008 \text{ Gflop/s}$  (60 FP units x (8+8) Flops/cy x 1.05 GHz)
- $P_{\text{max}}?$  → Observe LD/ST throughput maximum of 1 Load or 1 Store per cycle → 4 cy / 16 Flops →  $P_{\text{max}} = 252 \text{ Gflop/s}$  (25% of peak)

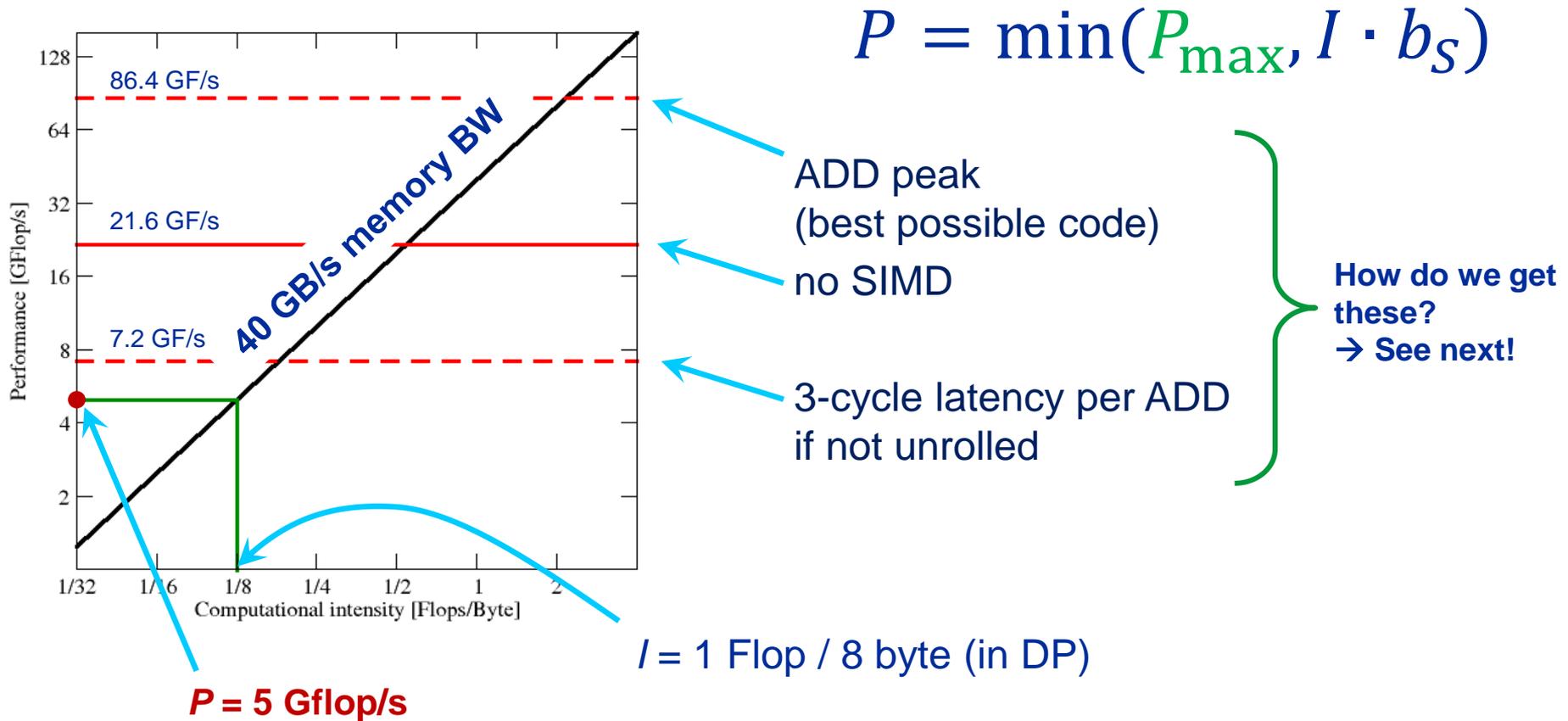
$$P = \min(P_{\text{max}}, I \cdot b_S) = \min(252, 8.0) \text{ GFlop/s} \\ = 8.0 \text{ GFlop/s}$$

# A not so simple Roofline example



Example: `do i=1,N; s=s+a(i); enddo`

in double precision on a 2.7 GHz Sandy Bridge socket @ “large” N

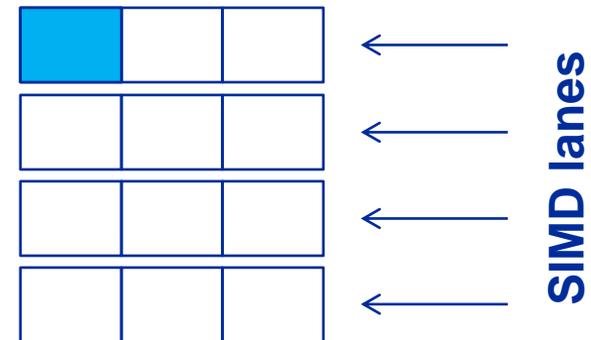




## Plain scalar code, no SIMD

```
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:



→ 1/12 of ADD peak



## Scalar code, 3-way unrolling

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

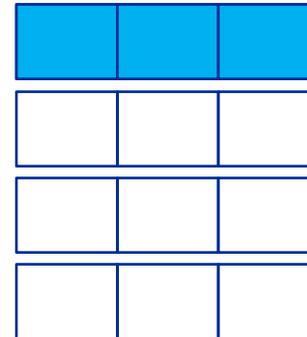
loop:

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

```
ADD r1.0 ← r1.0+r4.0  
ADD r2.0 ← r2.0+r5.0  
ADD r3.0 ← r3.0+r6.0
```

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

ADD pipes utilization:



→ 1/4 of ADD peak

# Applicable peak for the summation loop



## SIMD-vectorized, 3-way unrolled

LOAD [r1.0, ..., r1.3] ← [0, 0]

LOAD [r2.0, ..., r2.3] ← [0, 0]

LOAD [r3.0, ..., r3.3] ← [0, 0]

i ← 1

loop:

LOAD [r4.0, ..., r4.3] ← [a(i), ..., a(i+3)]

LOAD [r5.0, ..., r5.3] ← [a(i+4), ..., a(i+7)]

LOAD [r6.0, ..., r6.3] ← [a(i+8), ..., a(i+11)]

ADD r1 ← r1+r4

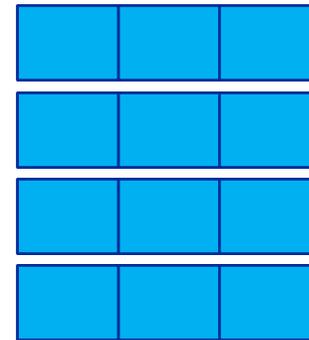
ADD r2 ← r2+r5

ADD r3 ← r3+r6

i+=12 →? loop

result ← r1.0+r1.1+...+r3.2+r3.3

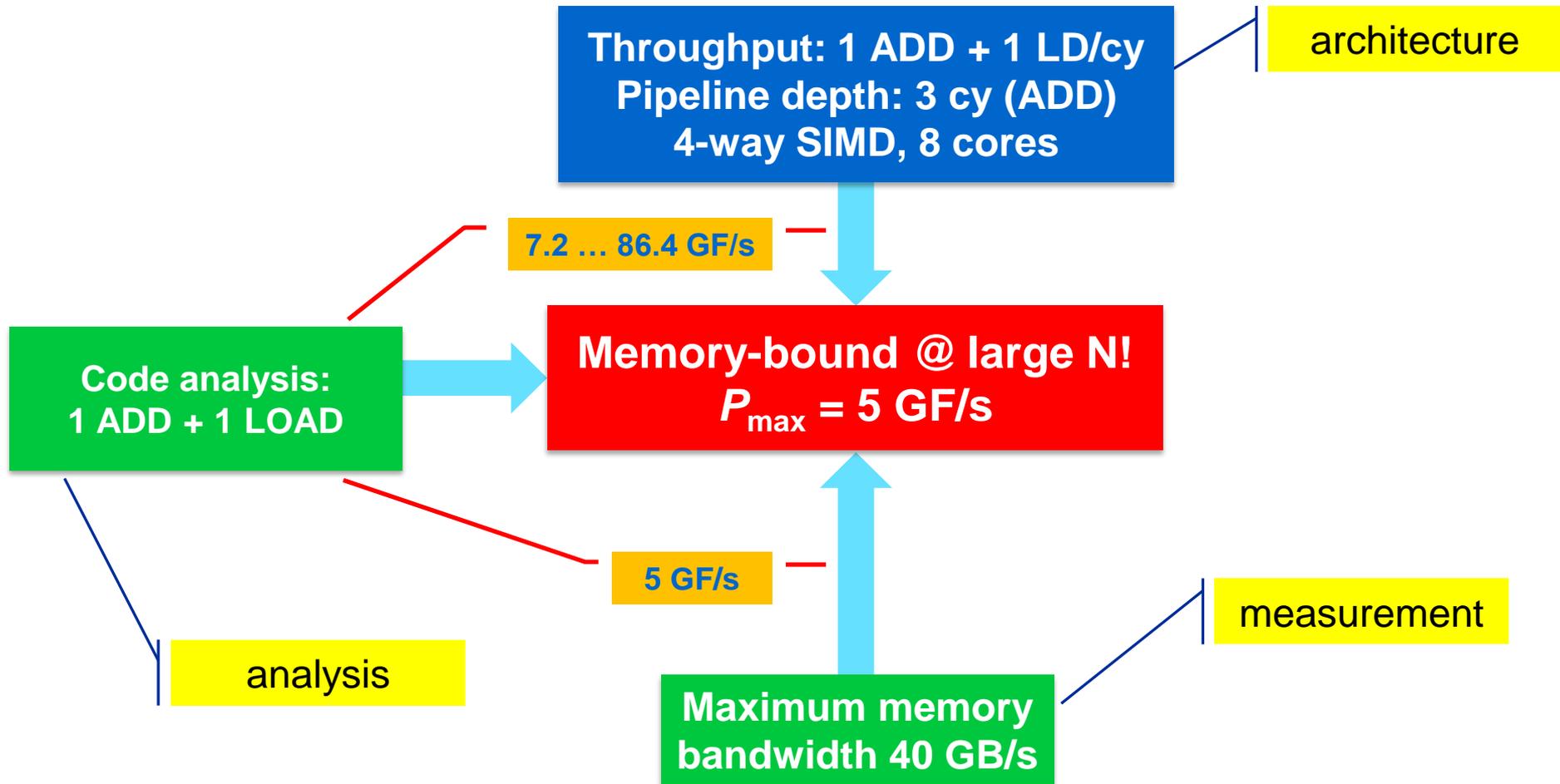
ADD pipes utilization:



→ ADD peak



... on the example of `do i=1,N; s=s+a(i); enddo`



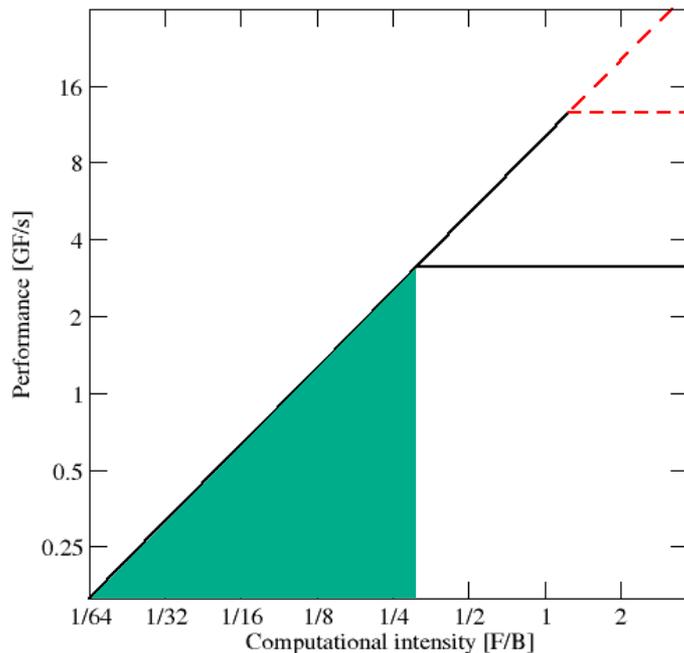


- **The roofline formalism is based on some (crucial) assumptions:**
  - There is a clear concept of “work” vs. “traffic”
    - “work” = flops, updates, iterations...
    - “traffic” = required data to do “work”
  - **Attainable bandwidth of code = input parameter!** Determine effective bandwidth via simple streaming benchmarks to model more complex kernels and applications
  - **Data transfer and core execution overlap perfectly!**
  - **Slowest data path is modeled only;** all others are assumed to be infinitely fast
  - If data transfer is the limiting factor, the **bandwidth** of the slowest data path can be **utilized to 100%** (“saturation”)
  - Latency effects are ignored, i.e. **perfect streaming mode**



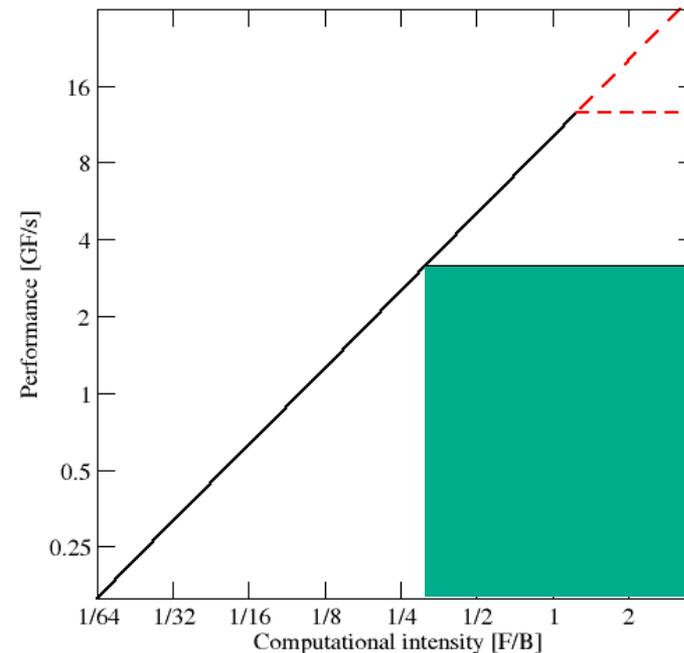
## Bandwidth-bound (simple case)

- Accurate traffic calculation (write-allocate, strided access, ...)
- Practical  $\neq$  theoretical BW limits
- **Erratic access patterns**



## Core-bound (may be complex)

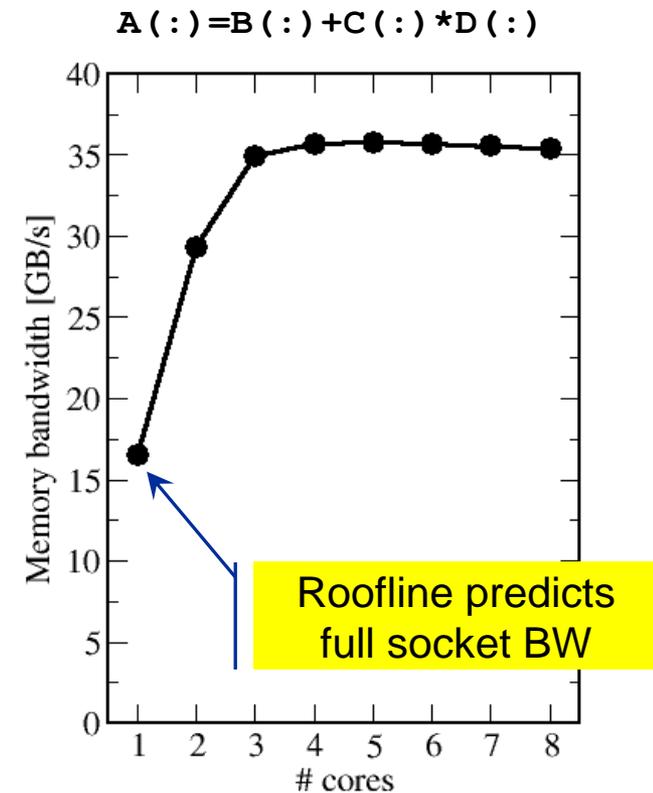
- **Multiple bottlenecks:** LD/ST, arithmetic, pipelines, SIMD, execution ports
- **Limit is linear in # of cores**

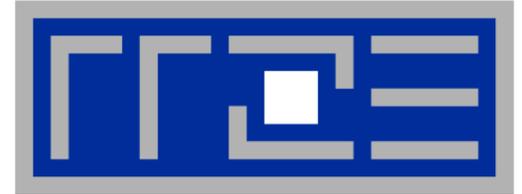


- **Saturation effects** in multicore chips are not explained
  - Reason: “saturation assumption”
  - Cache line transfers and core execution do sometimes not overlap perfectly
  - Only increased “pressure” on the memory interface can saturate the bus  
→ need more cores!

- **ECM model** gives more insight:

G. Hager, J. Treibig, J. Habich, and G. Wellein: Exploring performance and power properties of modern multicore chips via simple machine models.  
Submitted. Preprint: [arXiv:1208.2908](https://arxiv.org/abs/1208.2908)





**Case study:  
OpenMP-parallel sparse matrix-vector  
multiplication (part 2)**

**Putting Roofline to use where it should not work**



- **Sparse MVM in double precision w/ CRS data storage:**

```

do i = 1, Nr
  do j = row_ptr(i), row_ptr(i+1) - 1
    C(i) = C(i) + val(j) * B(col_idx(j))
  enddo
enddo
    
```

- **DP CRS comp. intensity**

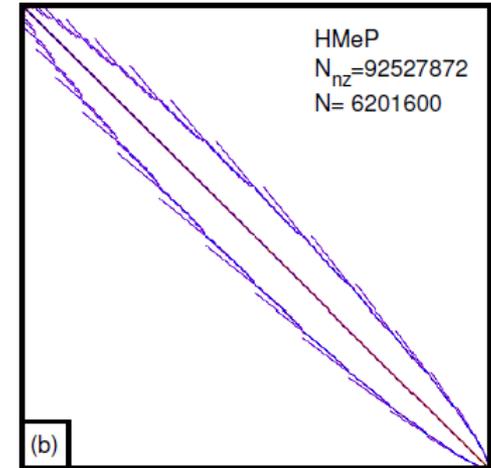
- $\kappa$  quantifies extra traffic for loading RHS more than once

$$\begin{aligned}
 I_{\text{CRS}} &= \frac{2 \text{ Flops}}{12 + 24/N_{\text{nzr}} + \kappa \text{ Byte}} \\
 &= \left( 6 + \frac{12}{N_{\text{nzr}}} + \frac{\kappa}{2} \right)^{-1} \frac{\text{Flops}}{\text{Byte}}
 \end{aligned}$$

- Expected performance =  $b_S \times I_{\text{CRS}}$
- Determine  $\kappa$  by measuring performance and actual memory bandwidth
  - Maximum memory BW may not be achieved with spMVM

## Analysis for HMeP matrix on Nehalem EP socket

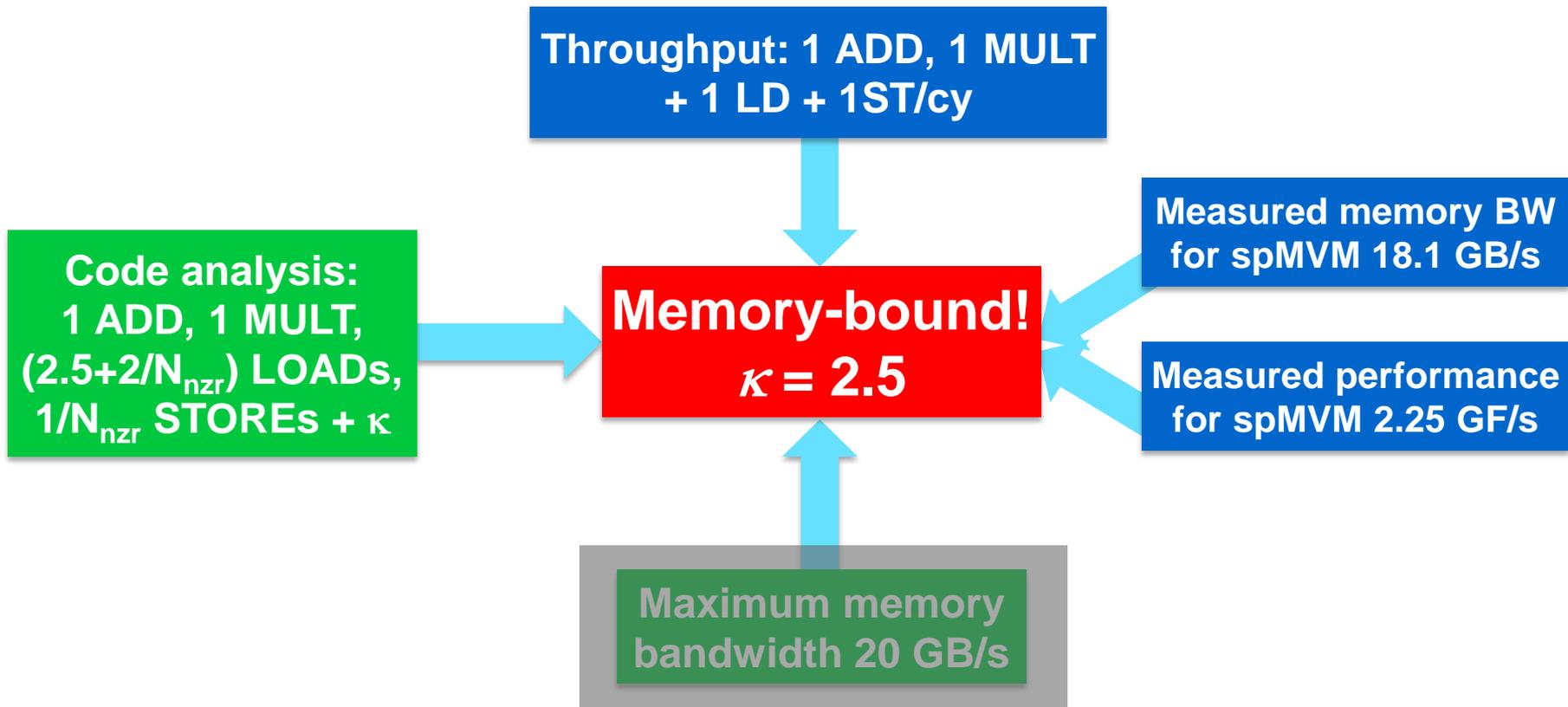
- BW used by spMVM kernel  $b = 18.1$  GB/s  $\rightarrow$  should get  $\approx 2.66$  Gflop/s spMVM performance if  $\kappa = 0$
- Measured spMVM performance = 2.25 Gflop/s
- Solve  $2.25$  Gflop/s =  $b \times I_{\text{CRS}}$  for  $\kappa \approx 2.5$ 
  - $\rightarrow$  37.5 extra bytes per row
  - $\rightarrow$  RHS is loaded 6 times from memory
  - $\rightarrow$  about 33% of BW goes into RHS

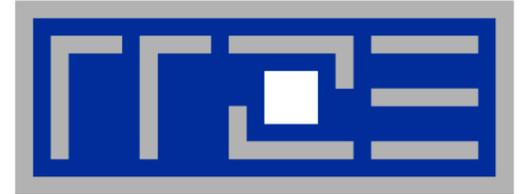


- **Conclusion:** Even if the roofline model does not work 100%, we can still learn something from the deviations



... on the example of spMVM with HMeP matrix





## **Case study: A 3D Jacobi smoother**

**The basics in two dimensions**

**Roofline performance analysis and modeling**



- Laplace equation in 2D:  $\Delta\Phi = 0$
- **Solve** with Dirichlet boundary conditions using Jacobi iteration scheme:

```

double precision, dimension(0:imax+1,0:kmax+1,0:1) :: phi
integer :: t0,t1
t0 = 0 ; t1 = 1
do it = 1,itmax      ! choose suitable number of sweeps
  do k = 1,kmax
    do i = 1,imax
      ! four flops, one store, four loads
      phi(i,k,t1) = ( phi(i+1,k,t0) + phi(i-1,k,t0)
                    + phi(i,k+1,t0) + phi(i,k-1,t0) ) * 0.25
    enddo
  enddo
  ! swap arrays
  i = t0 ; t0=t1 ; t1=i
enddo

```

Re-use when computing  $\text{phi}(i+2,k,t1)$

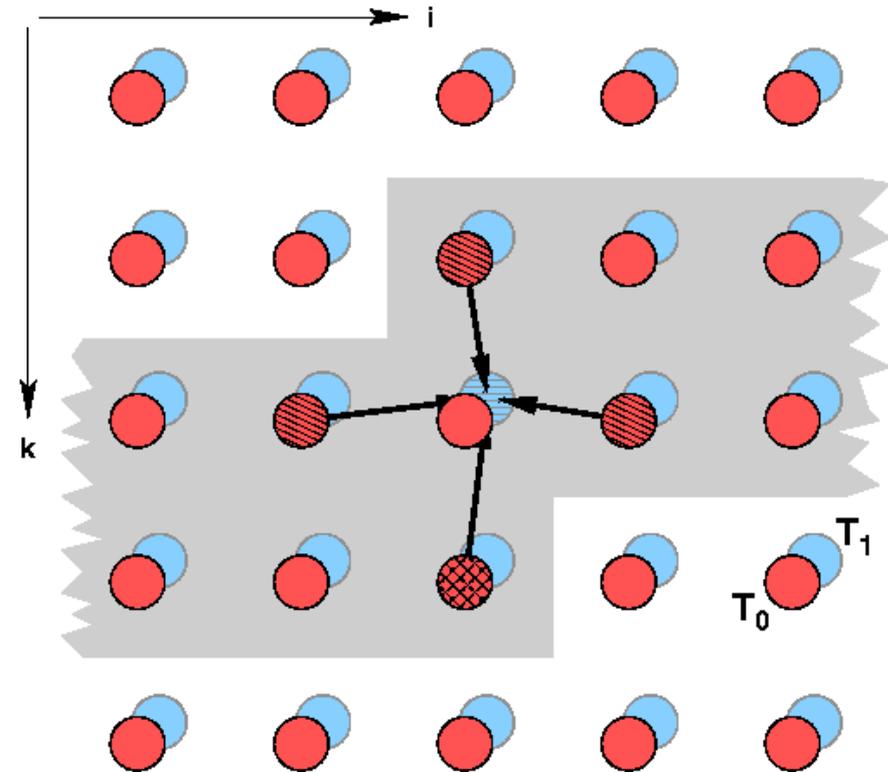
**Naive balance (incl. write allocate):**

$\text{phi}(:, :, t0)$ : 3 LD +  
 $\text{phi}(:, :, t1)$ : 1 ST+ 1LD

→  $B_C = 5 W / 4 \text{ FLOPs} = 1.25 W / F$

**WRITE ALLOCATE:**  
 LD + ST  $\text{phi}(i, k, t1)$

- Modern cache subsystems may further reduce memory traffic  
→ “layer conditions”



If cache is large enough to hold at least 2 rows (shaded region): Each  $\text{phi}(:, :, t_0)$  is loaded once from main memory and re-used 3 times from cache:

$$\text{phi}(:, :, t_0): 1 \text{ LD} + \text{phi}(:, :, t_1): 1 \text{ ST} + 1 \text{ LD} \\ \rightarrow B_C = 3W / 4F = 0.75W / F$$

If cache is too small to hold one row:  
 $\text{phi}(:, :, t_0): 2 \text{ LD} + \text{phi}(:, :, t_1): 1 \text{ ST} + 1 \text{ LD}$   
 $\rightarrow B_C = 5W / 4F = 1.25W / F$



- **Alternative implementation (“Macho FLOP version”)**

```
do k = 1, kmax
  do i = 1, imax
    phi(i, k, t1) = 0.25 * phi(i+1, k, t0) + 0.25 * phi(i-1, k, t0)
                  + 0.25 * phi(i, k+1, t0) + 0.25 * phi(i, k-1, t0)
  enddo
enddo
```

- **MFlops/sec increases by 7/4 but time to solution remains the same**
- **Better metric (for many iterative stencil schemes):**  
**Lattice Site Updates per Second (LUPs/sec)**

**2D Jacobi example: Compute LUPs/sec metric via**

$$P[LUPs / s] = \frac{it_{\max} \cdot i_{\max} \cdot k_{\max}}{T_{\text{wall}}}$$



- 3D sweep:

```
do k=1,kmax
  do j=1,jmax
    do i=1,imax
      phi(i,j,k,t1) = 1/6. * (phi(i-1,j,k,t0)+phi(i+1,j,k,t0) &
        + phi(i,j-1,k,t0)+phi(i,j+1,k,t0) &
        + phi(i,j,k-1,t0)+phi(i,j,k+1,t0))
    enddo
  enddo
enddo
```

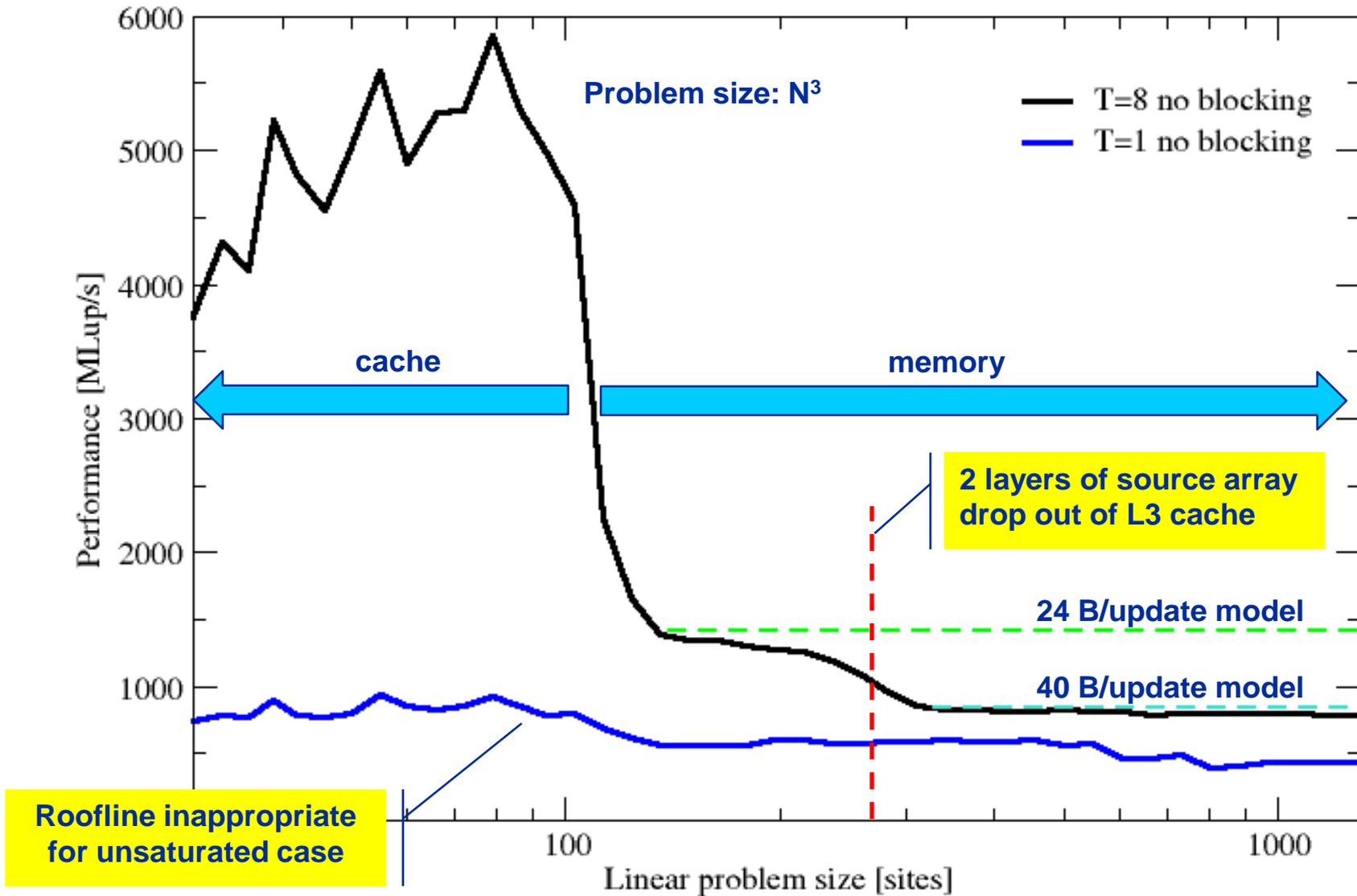
- Best case balance: 1 LD phi(i,j,k+1,t0)  
 1 ST + 1 write allocate phi(i,j,k,t1)  
 6 flops

→  $B_C = 0.5 \text{ W/F (24 bytes/LUP)}$

- No 2-layer condition but 2 rows fit:  $B_C = 5/6 \text{ W/F (40 bytes/LUP)}$
- Worst case (2 rows do not fit):  $B_C = 7/6 \text{ W/F (56 bytes/LUP)}$

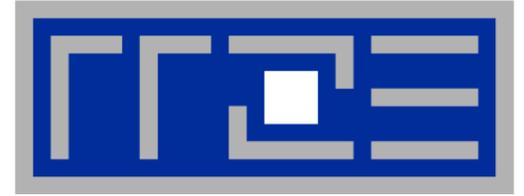
# 3D Jacobi solver

Performance of vanilla code on one Sandy Bridge chip (8 cores)





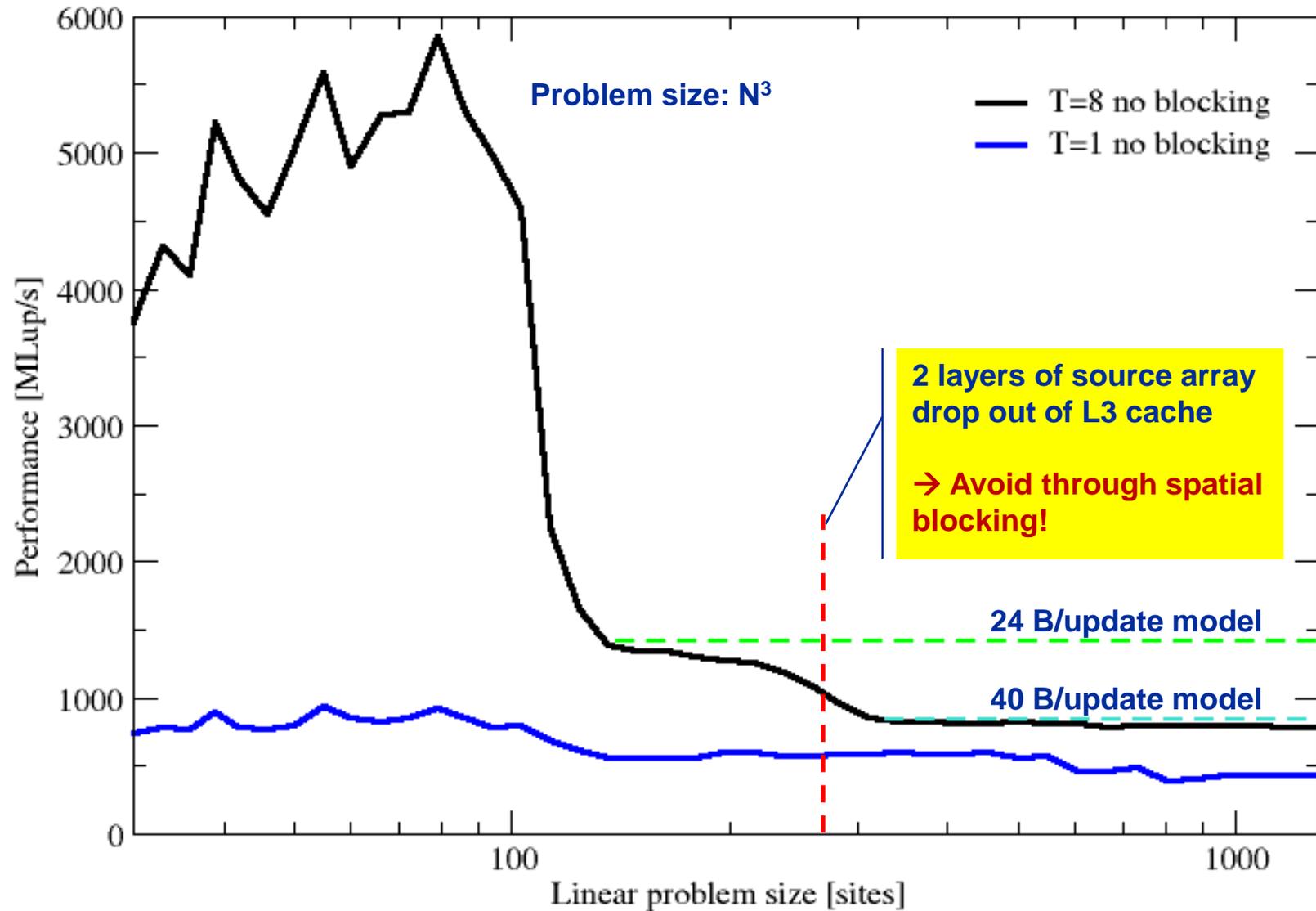
- We have **made sense** of the **memory-bound performance vs. problem size**
  - “Layer conditions” lead to **predictions of code balance**
  - Achievable memory bandwidth is input parameter
  
- **The model works only if the bandwidth is “saturated”**
  - In-cache modeling is more involved
  
- **Optimization == reducing the code balance by code transformations**
  - See below



# **Data access optimizations**

**Case study: Optimizing the 3D Jacobi solver**

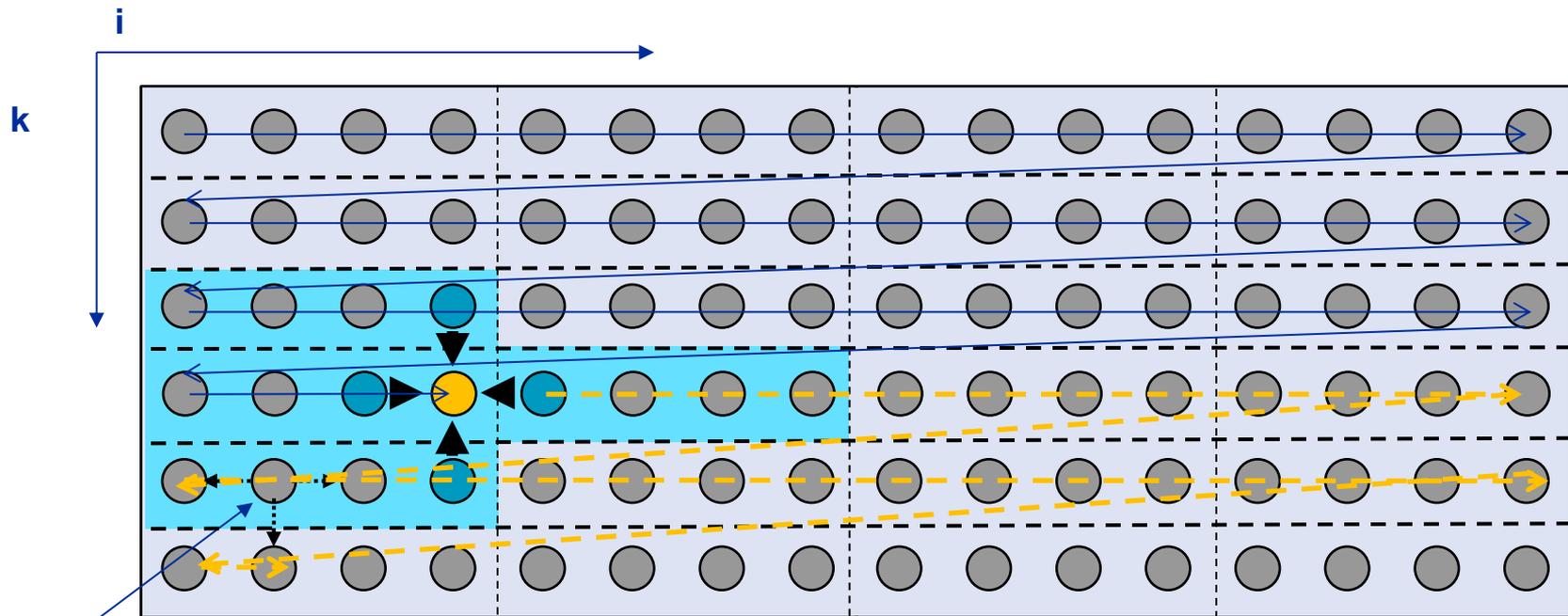
# Remember the 3D Jacobi solver on Sandy Bridge?





## Assumptions:

- cache can hold 32 elements (16 for each array)
- Cache line size is 4 elements
- Perfect eviction strategy for source array

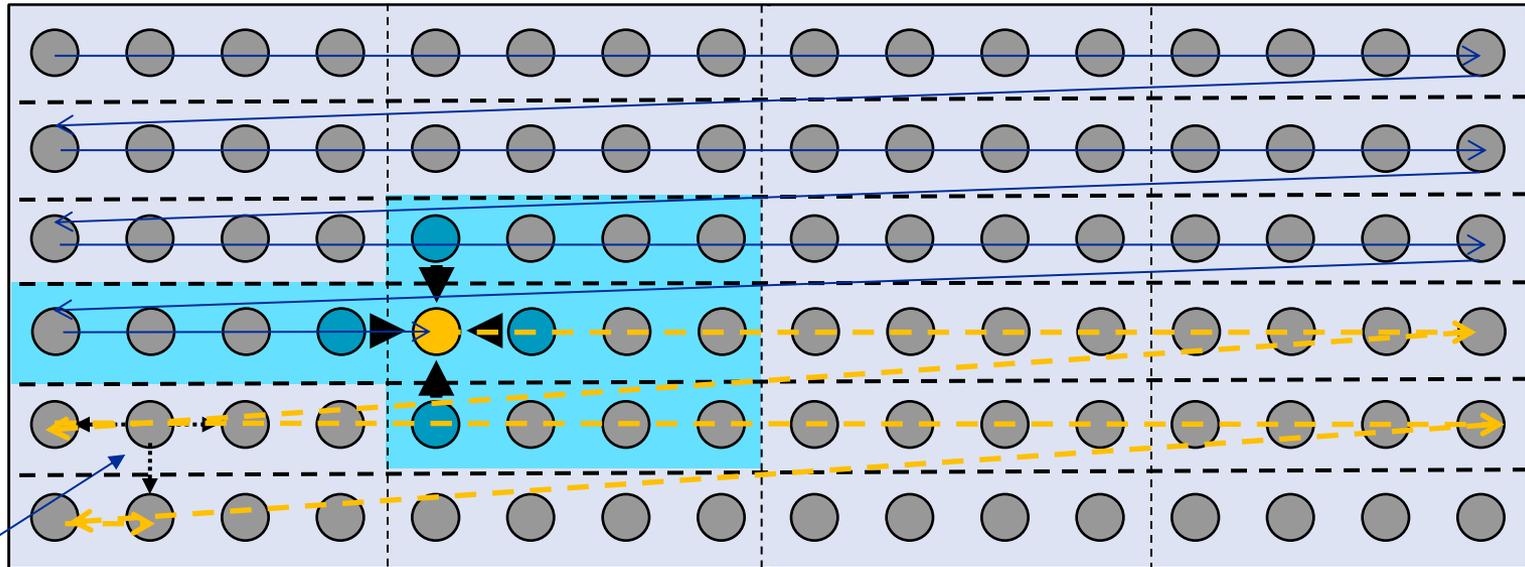


This element is needed for three more updates; but 29 updates happen before this element is used for the last time



## Assumptions:

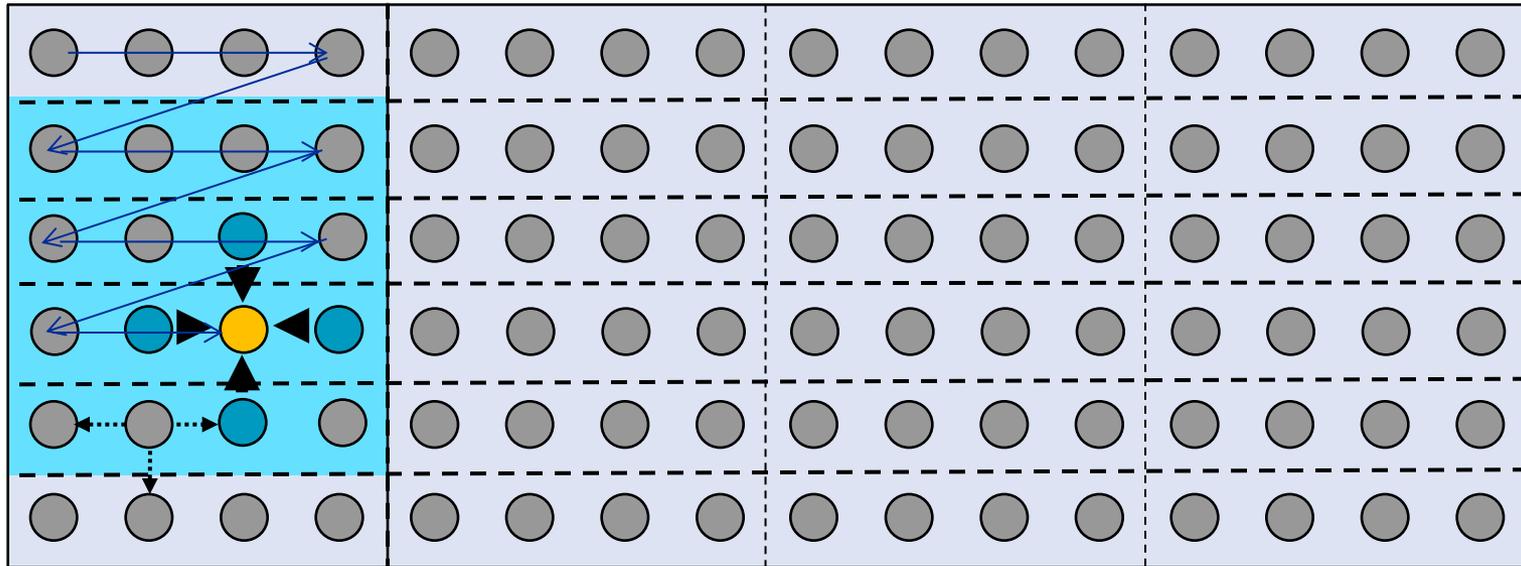
- cache can hold 32 elements (16 for each array)
- Cache line size is 4 elements
- Perfect eviction strategy for source array



**This element is needed for three more updates but has been evicted**



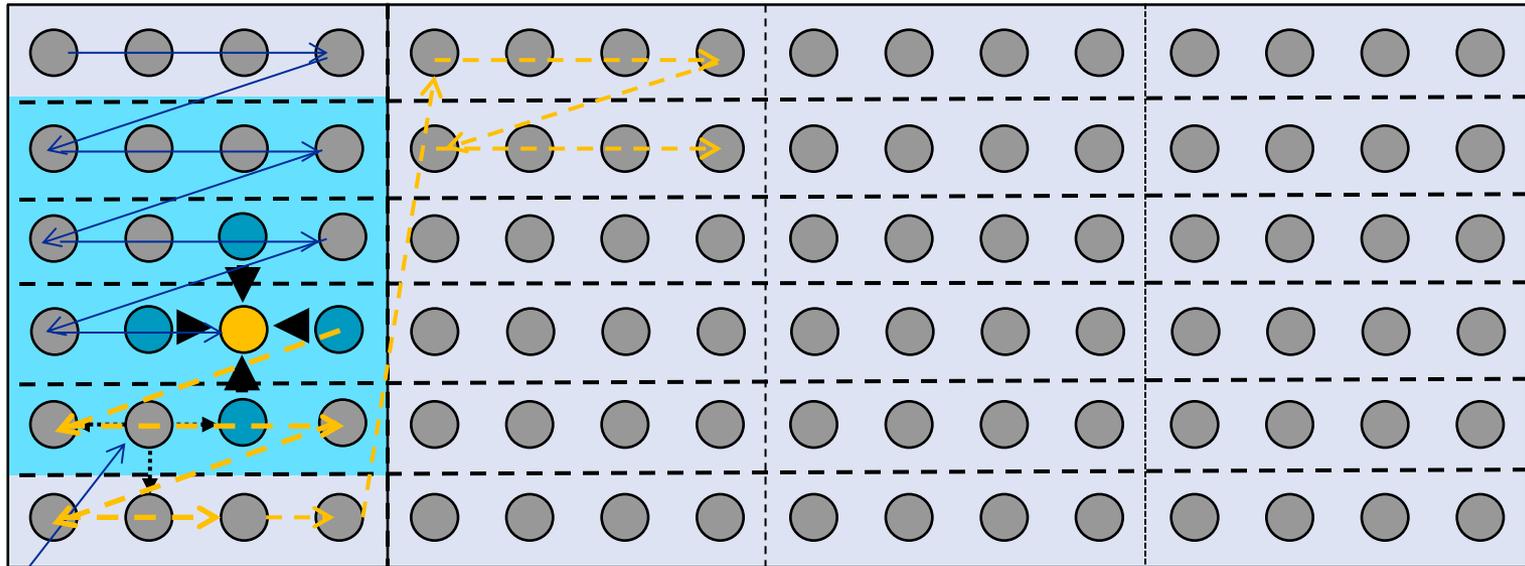
- **Divide system into blocks**
- **Update block after block**
- **Same performance as if three complete rows of the systems fit into cache**



- **Some excess traffic at boundaries may be unavoidable**



- **Spatial blocking reorders traversal of data to account for the data update rule of the code**
- **Elements stay sufficiently long in cache to be fully reused**
- **Spatial blocking improves temporal locality!**  
(Continuous access in inner loop ensures spatial locality)



**This element remains in cache until it is fully used (only 6 updates happen before last use of this element)**



## Implementation:

```
do ioffset=1,imax,iblock
  do joffset=1,jmax,jblock
    do k=1,kmax
      do j=joffset, min(jmax,joffset+jblock-1)
        do i=ioffset, min(imax,ioffset+iblock-1)
          phi(i,j,k,t1) = ( phi(i-1,j,k,t0)+phi(i+1,j,k,t0)
                        + ... + phi(i,j,k-1,t0)+phi(i,j,k+1,t0) )/6.d0
        enddo
      enddo
    enddo
  enddo
enddo
```

Diagram annotations:

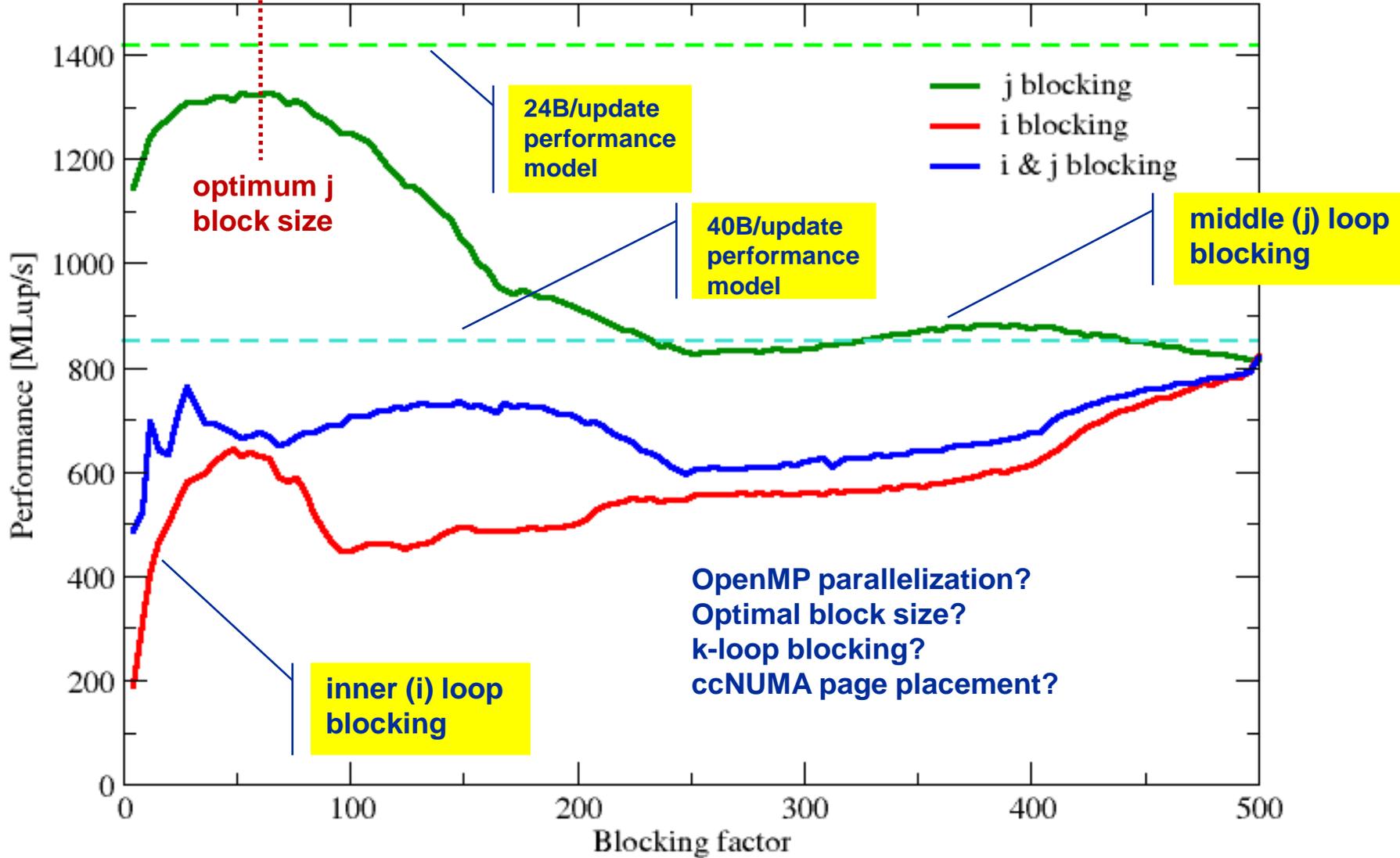
- A yellow box labeled "loop over i-blocks" has a line pointing to the `do ioffset=1,imax,iblock` line.
- A yellow box labeled "loop over j-blocks" has a line pointing to the `do joffset=1,jmax,jblock` line.

## Guidelines:

- Blocking of inner loop levels (traversing continuously through main memory)
- **Blocking sizes** large enough to fulfill “**layer condition**”
- Cache size is a hard limit!
- Blocking loops may have some impact on ccNUMA page placement

# 3D Jacobi solver (problem size $500^3$ )

Blocking different loop levels (8 cores Sandy Bridge)





- **Intel x86:** NT stores are **packed SIMD** stores with **16-byte aligned** address
  - Sometimes hard to apply
- **AMD x86:** **Scalar NT** stores **without alignment** restrictions available
- **Options for using NT stores**
  - Let the compiler decide → unreliable
  - Use compiler options
    - Intel: `-opt-streaming-stores never|always|auto`
  - Use compiler directives
    - Intel: `!DIR$ vector [non]temporal`
    - Cray: `!DIR$ LOOP_INFO cache[_nt](...)`
- **Compiler must be able to “prove” that the use of SIMD and NT stores is “safe”!**
  - “**line update kernel**” concept: Make critical loop its own subroutine



## Line update kernel (separate compilation unit or `-fno-inline`):

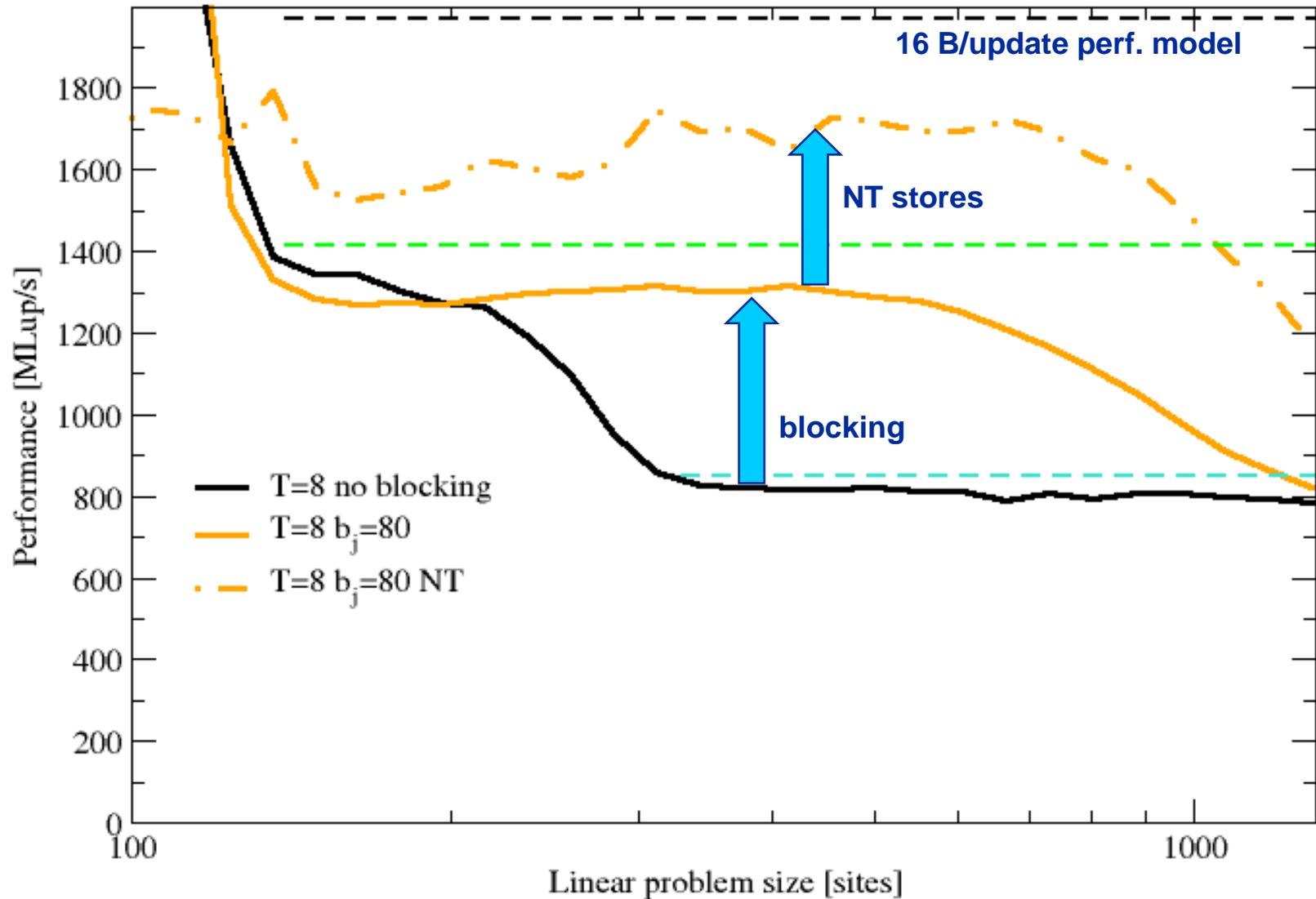
```
subroutine jacobi_line(d,s,top,bottom,front,back,n)
  integer :: n,i,start
  double precision, dimension(*) :: d,s,top,bottom,front,back
  double precision, parameter :: oos=1.d0/6.d0
  !DEC$ VECTOR NONTEMPORAL
  do i=2,n-1
    d(i) = oos*(s(i-1)+s(i+1)+top(i)+bottom(i)+front(i)+back(i))
  enddo
end subroutine
```

## Main loop:

```
do joffset=1,jmax,jblock
  do k=1,kmax
    do j=joffset, min(jmax,joffset+jblock-1)
      call jacobi_line(phi(1,j,k,t1),phi(1,j,k,t0),phi(1,j,k-1,t0), &
        phi(1,j,k+1,t0),phi(1,j-1,k,t0),phi(1,j+1,k,t0)
        ,size)
    enddo
  enddo
enddo
```

# 3D Jacobi solver

*Spatial blocking + nontemporal stores*

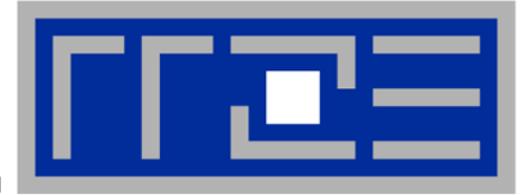




- **“What part of the data comes from where”** is a crucial question
- **Avoiding slow data paths == re-establishing the most favorable layer condition**
- **Improved code showed the speedup predicted by the model**
- **Optimal blocking factor can be estimated**
  - Be guided by the cache size the layer condition
  - No need for exhaustive scan of “optimization space”



- **Preliminaries**
- **Introduction to multicore architecture**
  - Cores, caches, chips, sockets, ccNUMA, SIMD
- **LIKWID tools**
- **Microbenchmarking for architectural exploration**
  - Streaming benchmarks: throughput mode
  - Streaming benchmarks: work sharing
  - Roadblocks for scalability: Saturation effects and OpenMP overhead
- **Node-level performance modeling**
  - The Roofline Model
  - Case study: 3D Jacobi solver and model-guided optimization
- **Optimal resource utilization**
  - SIMD parallelism
  - ccNUMA

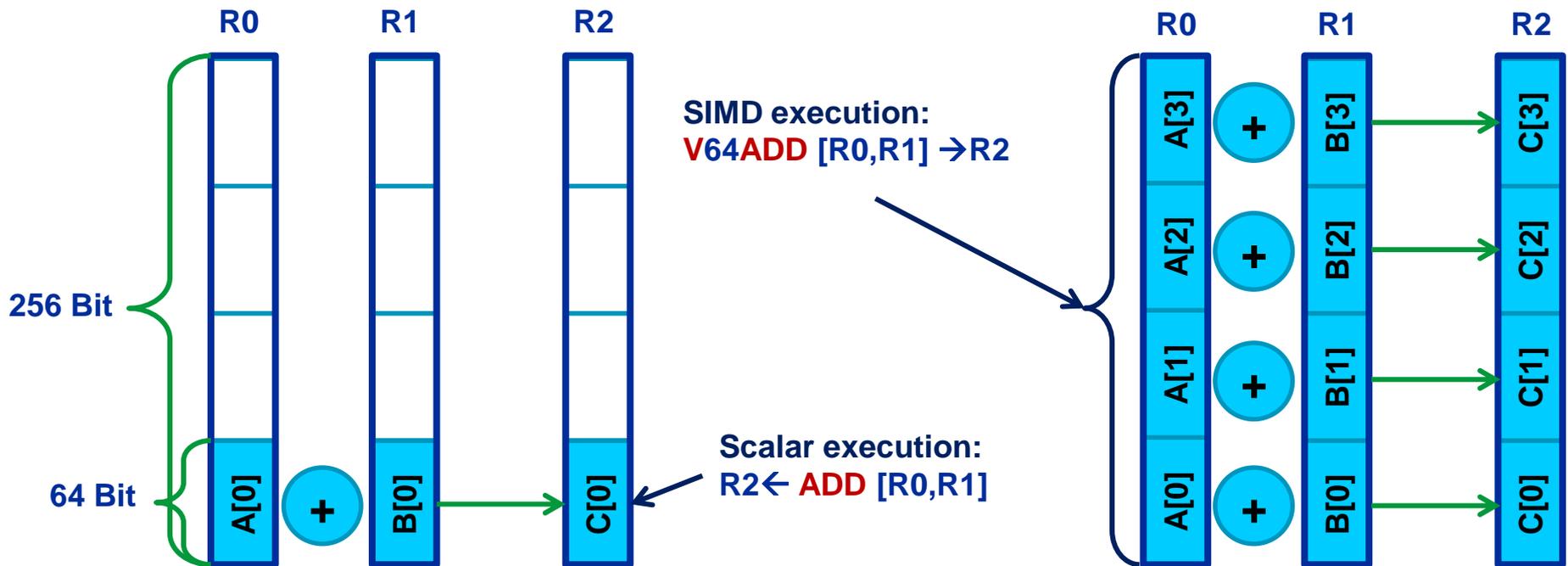


## **Optimal utilization of parallel resources**

Exploiting SIMD parallelism and reading assembly code  
Programming for ccNUMA memory architecture



- **Single Instruction Multiple Data (SIMD)** operations allow the **concurrent execution of the same operation on “wide” registers.**
- **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
- **Adding two registers holding double precision floating point operands**



- Steps (**done by the compiler**) for “SIMD processing”

```
for(int i=0; i<n;i++)  
    C[i]=A[i]+B[i];
```

“Loop unrolling”

```
for(int i=0; i<n;i+=4){  
    C[i]  =A[i]  +B[i];  
    C[i+1]=A[i+1]+B[i+1];  
    C[i+2]=A[i+2]+B[i+2];  
    C[i+3]=A[i+3]+B[i+3];  
    //remainder loop handling
```

Load 256 Bits starting from address of A[i] to register R0

Add the corresponding 64 Bit entries in R0 and R1 and store the 4 results to R2

Store R2 (256 Bit) to address starting at C[i]

**LABEL1:**

```
VLOAD R0 ← A[i]  
VLOAD R1 ← B[i]  
V64ADD[R0,R1] → R2  
VSTORE R2 → C[i]  
i ← i+4  
i < (n-4)? JMP LABEL1  
//remainder loop handling
```



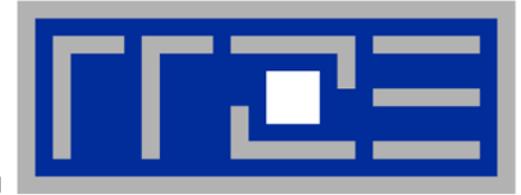
- **No SIMD vectorization for loops with data dependencies:**

```
for(int i=0; i<n;i++)  
    A[i]=A[i-1]*s;
```

- **“Pointer aliasing” may prevent SIMDification**

```
void scale_shift(double *A, double *B, double *C, int n) {  
    for(int i=0; i<n; ++i)  
        C[i] = A[i] + B[i];  
}
```

- C/C++ allows that  $A \rightarrow \&C[-1]$  and  $B \rightarrow \&C[-2]$   
→  $C[i] = C[i-1] + C[i-2]$ : **dependency** → **No SIMD**
- **If “pointer aliasing” is not used**, tell it to the compiler, e.g. use **-fno-alias** switch for Intel compiler → **SIMD**



# **Reading x86 assembly code and exploiting SIMD parallelism**

**Understanding SIMD execution by inspecting assembly code**

**SIMD vectorization how-to**

**Intel compiler options and features for SIMD**



## Why check the assembly code?

- **Sometimes the only way to make sure the compiler “did the right thing”**
  - Example: “LOOP WAS VECTORIZED” message is printed, but Loads & Stores may still be scalar!

- **Get the assembler code (Intel compiler):**

```
icc -S -O3 -xHost triad.c -o a.out
```

- **Disassemble Executable:**

```
objdump -d ./a.out | less
```

**The x86 ISA is documented in:**

**Intel Software Development Manual (SDM) 2A and 2B  
AMD64 Architecture Programmer's Manual Vol. 1-5**



## 16 general Purpose Registers (**64bit**):

`rax, rbx, rcx, rdx, rsi, rdi, rsp, rbp, r8-r15`

alias with eight 32 bit register set:

`eax, ebx, ecx, edx, esi, edi, esp, ebp`

## Floating Point **SIMD** Registers:

`xmm0-xmm15` SSE (128bit) alias with 256-bit registers

`ymm0-ymm15` AVX (256bit)

SIMD instructions are distinguished by:

**AVX (VEX) prefix:**

`v`

**Operation:**

`mul, add, mov`

**Modifier:**

nontemporal (`nt`), unaligned (`u`), aligned (`a`), high (`h`)

**Width:**

scalar (`s`), packed (`p`)

**Data type:**

single (`s`), double (`d`)

# Case Study: Simplest code for the summation of the elements of a vector (single precision)



```
float sum = 0.0;

for (int j=0; j<size; j++){
    sum += data[j];
}
```

To get object code use `objdump -d` on object file or executable or compile with `-S`

## Instruction code:

```
401d08:  f3 0f 58 04 82
401d0d:  48 83 c0 01
401d11:  39 c7
401d13:  77 f3
```

```
addss  xmm0, [rdx + rax * 4]
add    rax, 1
cmp    edi, eax
ja     401d08
```

Instruction address

Opcodes

Assembly code

# Summation code (single precision): Improvements



```
1:
addss xmm0, [rsi + rax * 4]
add    rax, 1
cmp    eax,edi
js 1b
```

3 cycles add  
pipeline  
latency

Unrolling with sub-sums to break up  
register dependency

```
1:
vaddps ymm0, [rsi + rax * 4]
vaddps ymm1, [rsi + rax * 4 + 32]
vaddps ymm2, [rsi + rax * 4 + 64]
vaddps ymm3, [rsi + rax * 4 + 96]
add    rax, 32
cmp    eax,edi
js 1b
```

AVX SIMD vectorization

```
1:
addss xmm0, [rsi + rax * 4]
addss xmm1, [rsi + rax * 4 + 4]
addss xmm2, [rsi + rax * 4 + 8]
addss xmm3, [rsi + rax * 4 + 12]
add    rax, 4
cmp    eax,edi
js 1b
```



## Alternatives:

- The **compiler** does it for you (but: aliasing, alignment, language)
- Compiler directives (**pragmas**)
- Alternative **programming models** for compute kernels (OpenCL, ispc)
- **Intrinsics** (restricted to C/C++)
- Implement directly in **assembler**

## To use **intrinsics** the following headers are available:

- `xmmintrin.h` (SSE)
- `pmmintrin.h` (SSE2)
- `immintrin.h` (AVX)
  
- `x86intrin.h` (all instruction set extensions)
- See next slide for an example

## Example: array summation using C intrinsics (SSE, single precision)



```
__m128 sum0, sum1, sum2, sum3;
__m128 t0, t1, t2, t3;
float scalar_sum;
sum0 = _mm_setzero_ps();
sum1 = _mm_setzero_ps();
sum2 = _mm_setzero_ps();
sum3 = _mm_setzero_ps();
```

```
sum0 = _mm_add_ps(sum0, sum1);
sum0 = _mm_add_ps(sum0, sum2);
sum0 = _mm_add_ps(sum0, sum3);
sum0 = _mm_hadd_ps(sum0, sum0);
sum0 = _mm_hadd_ps(sum0, sum0);

_mm_store_ss(&scalar_sum, sum0);
```

```
for (int j=0; j<size; j+=16){
    t0 = _mm_loadu_ps(data+j);
    t1 = _mm_loadu_ps(data+j+4);
    t2 = _mm_loadu_ps(data+j+8);
    t3 = _mm_loadu_ps(data+j+12);
    sum0 = _mm_add_ps(sum0, t0);
    sum1 = _mm_add_ps(sum1, t1);
    sum2 = _mm_add_ps(sum2, t2);
    sum3 = _mm_add_ps(sum3, t3);
}
```

# Example: array summation from intrinsics, instruction code



```
14: 0f 57 c9      xorps  %xmm1,%xmm1
17: 31 c0         xor    %eax,%eax
19: 0f 28 d1      movaps %xmm1,%xmm2
1c: 0f 28 c1      movaps %xmm1,%xmm0
1f: 0f 28 d9      movaps %xmm1,%xmm3
22: 66 0f 1f 44 00 00  nopw  0x0(%rax,%rax,1)
28: 0f 10 3e      movups (%rsi),%xmm7
2b: 0f 10 76 10   movups 0x10(%rsi),%xmm6
2f: 0f 10 6e 20   movups 0x20(%rsi),%xmm5
33: 0f 10 66 30   movups 0x30(%rsi),%xmm4
37: 83 c0 10      add    $0x10,%eax
3a: 48 83 c6 40   add    $0x40,%rsi
3e: 0f 58 df      addps  %xmm7,%xmm3
41: 0f 58 c6      addps  %xmm6,%xmm0
44: 0f 58 d5      addps  %xmm5,%xmm2
47: 0f 58 cc      addps  %xmm4,%xmm1
4a: 39 c7         cmp    %eax,%edi
4c: 77 da         ja     28 <compute_sum_SSE+0x18>
4e: 0f 58 c3      addps  %xmm3,%xmm0
51: 0f 58 c2      addps  %xmm2,%xmm0
54: 0f 58 c1      addps  %xmm1,%xmm0
57: f2 0f 7c c0   haddps %xmm0,%xmm0
5b: f2 0f 7c c0   haddps %xmm0,%xmm0
5f: c3           retq
```

Loop body



- **Intel compiler will try to use SIMD instructions when enabled to do so**

- “Poor man’s vector computing”
- Compiler can emit messages about vectorized loops (not by default):

```
plain.c(11): (col. 9) remark: LOOP WAS VECTORIZED.
```

- Use option `-vec_report3` to get full compiler output about which loops were vectorized and which were not and why (data dependencies!)
  - Some obstructions will prevent the compiler from applying vectorization even if it is possible
- You can use **source code directives** to provide more information to the compiler



- **The compiler will vectorize starting with `-O2`.**
- **To enable specific SIMD extensions use the `-x` option:**
  - **`-xSSE2`** vectorize for SSE2 capable machines

Available SIMD extensions:

**`SSE2`, `SSE3`, `SSSE3`, `SSE4.1`, `SSE4.2`, `AVX`**

- **`-xAVX`** on Sandy Bridge processors

Recommended option:

- **`-xHost`** will optimize for the architecture you compile on

On AMD Opteron: use plain `-O3` as the `-x` options may involve CPU type checks.



- **Controlling non-temporal stores (part of the SIMD extensions)**

- `-opt-streaming-stores` **always|auto|never**

**always** use NT stores, assume application is memory bound (use with caution!)

**auto** compiler decides when to use NT stores

**never** do not use NT stores unless activated by source code directive



1. **Countable**
2. **Single entry and single exit**
3. **Straight line code**
4. **No function calls (exception intrinsic math functions)**

## **Better performance with:**

1. **Simple inner loops with unit stride**
2. **Minimize indirect addressing**
3. **Align data structures (SSE 16 bytes, AVX 32 bytes)**
4. **In C use the restrict keyword for pointers to rule out aliasing**

## **Obstacles for vectorization:**

- **Non-contiguous memory access**
- **Data dependencies**



- Fine-grained control of loop vectorization
- Use `!DEC$` (Fortran) or `#pragma` (C/C++) sentinel to start a compiler directive
- `#pragma vector always`  
vectorize even if it seems inefficient (hint!)
- `#pragma novector`  
do not vectorize even if possible
- `#pragma vector nontemporal`  
use NT stores when allowed (i.e. alignment conditions are met)
- `#pragma vector aligned`  
specifies that all array accesses are aligned to 16-byte boundaries  
(**DANGEROUS!** You must not lie about this!)



- Since Intel Compiler 12.0 the **simd pragma** is available
- **#pragma simd** enforces vectorization where the other pragmas fail
- **Prerequisites:**
  - Countable loop
  - Innermost loop
  - Must conform to for-loop style of OpenMP worksharing constructs
- **There are additional clauses:** `reduction`, `vectorlength`, `private`
- **Refer to the compiler manual for further details**

```
#pragma simd reduction(+:x)  
  for (int i=0; i<n; i++) {  
    x = x + A[i];  
  }
```

- **NOTE:** Using the **#pragma simd** the compiler may generate incorrect code if the loop violates the vectorization rules!



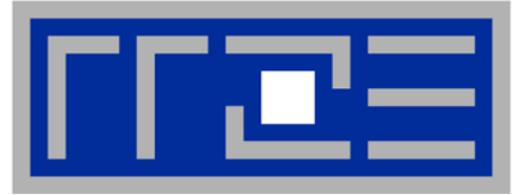
### ▪ **Alignment issues**

- Alignment of arrays with SSE (AVX) should be on 16-byte (32-byte) boundaries to **allow packed aligned loads and NT stores (for Intel processors)**
  - **AMD has a scalar nontemporal store instruction**
- Otherwise the compiler will revert to unaligned loads and not use NT stores – even if you say **vector nontemporal**
- Modern x86 CPUs have less (not zero) impact for misaligned LD/ST, but **Xeon Phi relies heavily on it!**
- How is manual alignment accomplished?

### ▪ **Dynamic allocation of aligned memory (align = alignment boundary):**

```
#define _XOPEN_SOURCE 600
#include <stdlib.h>

int posix_memalign(void **ptr,
                  size_t align,
                  size_t size);
```



# **Efficient parallel programming on ccNUMA nodes**

**Performance characteristics of ccNUMA nodes**

**First touch placement policy**

**C++ issues**

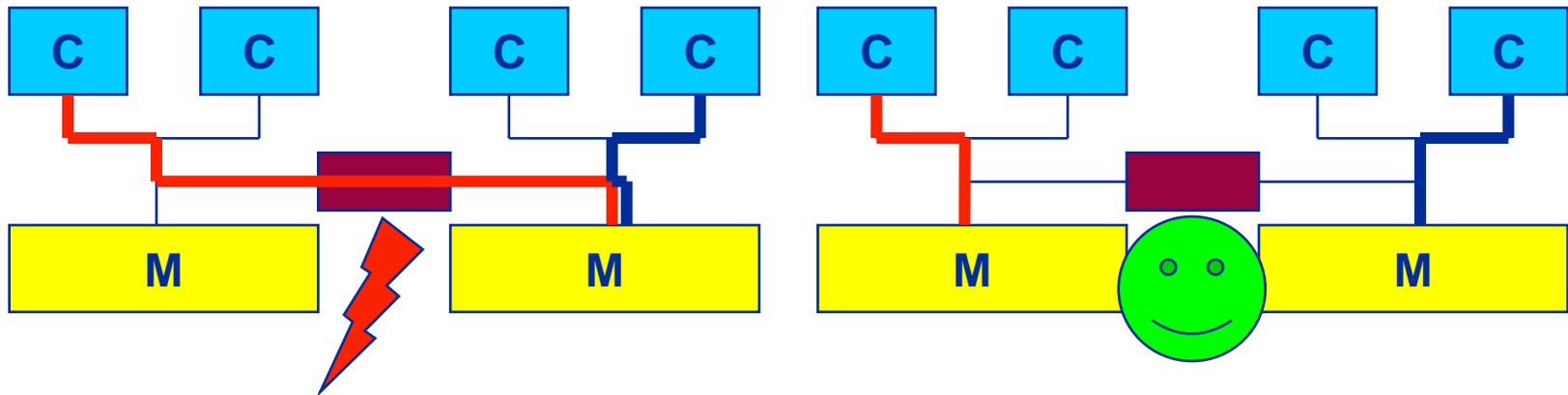
**ccNUMA locality and dynamic scheduling**

**ccNUMA locality beyond first touch**



## ■ ccNUMA:

- Whole memory is **transparently accessible** by all processors
  - but **physically distributed**
  - with **varying bandwidth and latency**
  - and **potential contention** (shared memory paths)
- **How do we make sure that memory access is always as "local" and "distributed" as possible?**



- Page placement is implemented in units of OS pages (often 4kB, possibly more)

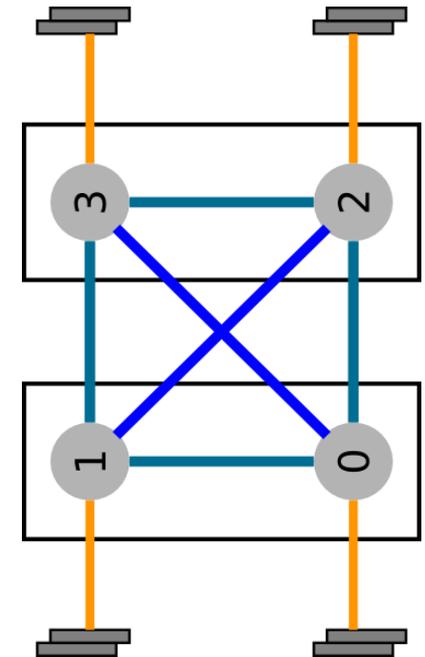
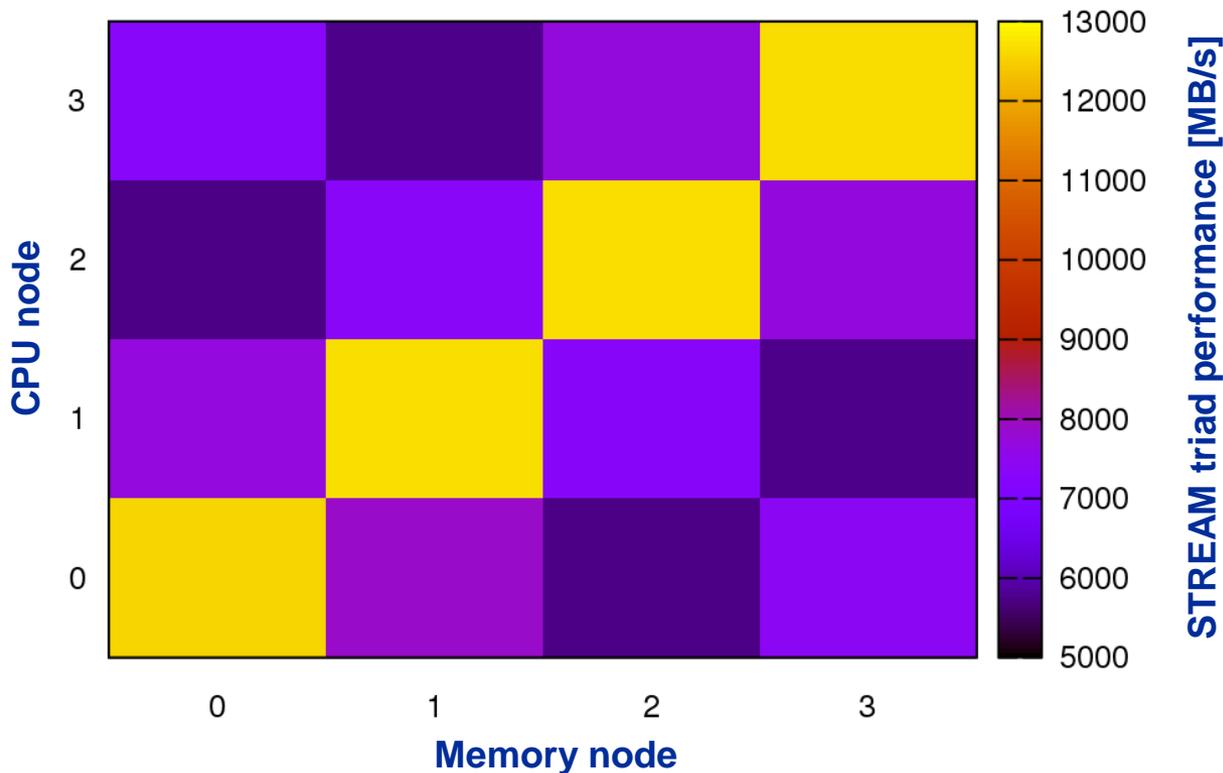
# Cray XE6 Interlagos node

4 chips, two sockets, 8 threads per ccNUMA domain



- **ccNUMA map: Bandwidth penalties for remote access**

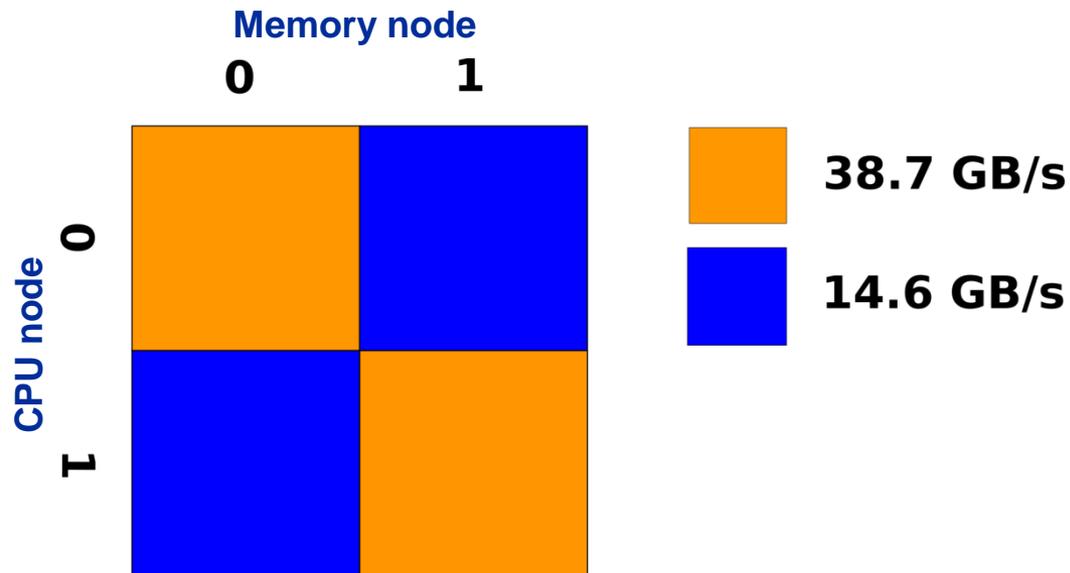
- Run 8 threads per ccNUMA domain (1 chip)
- Place memory in different domain → 4x4 combinations
- STREAM triad benchmark using nontemporal stores





- **General rule:**

The more ccNUMA domains, the larger the non-local access penalty





- **numactl** can influence the way a binary maps its memory pages:

```
numactl --membind=<nodes> a.out      # map pages only on <nodes>
      --preferred=<node> a.out      # map pages on <node>
                                       # and others if <node> is full
      --interleave=<nodes> a.out    # map pages round robin across
                                       # all <nodes>
```

- **Examples:**

```
for m in `seq 0 3`; do
    for c in `seq 0 3`; do
        env OMP_NUM_THREADS=8 \
            numactl --membind=$m --cpunodebind=$c ./stream
    enddo
enddo
```

ccNUMA map scan

```
env OMP_NUM_THREADS=4 numactl --interleave=0-3 \
    likwid-pin -c N:0,4,8,12 ./stream
```

- **But what is the default without numactl?**



- "Golden Rule" of ccNUMA:

**A memory page gets mapped into the local memory of the processor that first touches it!**

- Except if there is not enough local memory available
- This might be a problem, see later
- **Caveat: "touch" means "write", not "allocate"**
- **Example:**

```
double *huge = (double*)malloc(N*sizeof(double));
```

```
for(i=0; i<N; i++) // or i+=PAGE_SIZE  
    huge[i] = 0.0;
```

Memory not mapped here yet

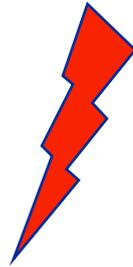
Mapping takes place here

- **It is sufficient to touch a single item to map the entire page**

- Most simple case: explicit initialization

```
integer,parameter :: N=10000000
double precision A(N), B(N)
```

```
A=0.d0
```



```
!$OMP parallel do
do i = 1, N
  B(i) = function ( A(i) )
end do
!$OMP end parallel do
```

```
integer,parameter :: N=10000000
double precision A(N),B(N)
```

```
!$OMP parallel
!$OMP do schedule(static)
```

```
do i = 1, N
```

```
  A(i)=0.d0
```

```
end do
```

```
!$OMP end do
```

```
...
```

```
!$OMP do schedule(static)
```

```
do i = 1, N
```

```
  B(i) = function ( A(i) )
```

```
end do
```

```
!$OMP end do
```

```
!$OMP end parallel
```

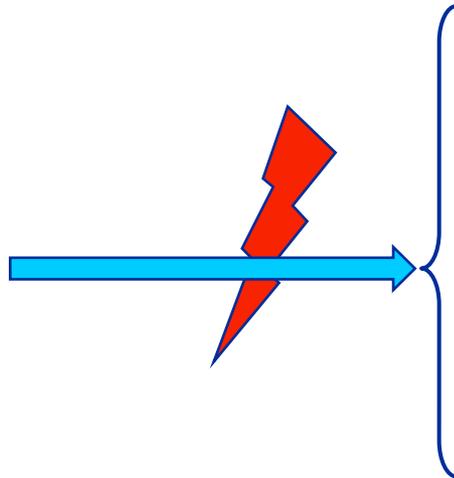


- Sometimes initialization is not so obvious: I/O cannot be easily parallelized, so “localize” arrays before I/O

```
integer,parameter :: N=10000000
double precision A(N), B(N)
```

```
READ(1000) A
```

```
!$OMP parallel do
do i = 1, N
  B(i) = function ( A(i) )
end do
!$OMP end parallel do
```



```
integer,parameter :: N=10000000
double precision A(N),B(N)
```

```
!$OMP parallel
!$OMP do schedule(static)
```

```
do i = 1, N
  A(i)=0.d0
```

```
end do
```

```
!$OMP end do
```

```
!$OMP single
```

```
READ(1000) A
```

```
!$OMP end single
```

```
!$OMP do schedule(static)
```

```
do i = 1, N
```

```
  B(i) = function ( A(i) )
```

```
end do
```

```
!$OMP end do
```

```
!$OMP end parallel
```





- **Required condition: OpenMP `loop schedule` of initialization must be the same as in all computational loops**
  - Only choice: **`static`**! Specify **`explicitly`** on all NUMA-sensitive loops, just to be sure...
  - Imposes some constraints on possible optimizations (e.g. load balancing)
  - Presupposes that all **`worksharing loops`** with the **`same loop length`** have the **`same thread-chunk mapping`**
  - If **`dynamic scheduling/tasking`** is unavoidable, more advanced methods may be in order
    - See below
- **How about `global objects`?**
  - Better not use them
  - If communication vs. computation is favorable, might consider **`properly placed copies`** of global data
- **C++: Arrays of objects and `std::vector<>` are by default initialized sequentially**
  - **`STL allocators`** provide an elegant solution



- **Don't forget that constructors tend to touch the data members of an object. Example:**

```
class D {
    double d;
public:
    D(double _d=0.0) throw() : d(_d) {}
    inline D operator+(const D& o) throw() {
        return D(d+o.d);
    }
    inline D operator*(const D& o) throw() {
        return D(d*o.d);
    }
    ...
};
```

→ placement problem with

```
D* array = new D[1000000];
```

# Coding for Data Locality:

## Parallel first touch for arrays of objects



- **Solution: Provide overloaded `D::operator new[]`**

```
void* D::operator new[](size_t n) {
    char *p = new char[n];    // allocate

    size_t i, j;

    #pragma omp parallel for private(j) schedule(...)
    for(i=0; i<n; i += sizeof(D))
        for(j=0; j<sizeof(D); ++j)
            p[i+j] = 0;
    return p;
}

void D::operator delete[](void* p) throw() {
    delete [] static_cast<char*>p;
}
```

parallel first touch

- **Placement of objects is then done automatically by the C++ runtime via “placement new”**

## Coding for Data Locality:

*NUMA allocator for parallel first touch in `std::vector<>`*



```
template <class T> class NUMA_Allocator {
public:
    T* allocate(size_type numObjects, const void
                *localityHint=0) {
        size_type ofs, len = numObjects * sizeof(T);
        void *m = malloc(len);
        char *p = static_cast<char*>(m);
        int i, pages = len >> PAGE_BITS;
#pragma omp parallel for schedule(static) private(ofs)
        for(i=0; i<pages; ++i) {
            ofs = static_cast<size_t>(i) << PAGE_BITS;
            p[ofs]=0;
        }
        return static_cast<pointer>(m);
    }
    ...
};
```

### Application:

```
vector<double, NUMA_Allocator<double> > x(10000000)
```



- If your code is cache-bound, you might not notice any locality problems
- Otherwise, bad locality **limits scalability at very low CPU numbers (whenever a node boundary is crossed)**
  - If the code makes good use of the memory interface
  - But there may also be a general problem in your code...
- Running with **numactl --interleave** might give you a hint
  - See later
- Consider using performance counters
  - **LIKWID-perfctr** can be used to measure nonlocal memory accesses
  - Example for Intel Westmere dual-socket system (Core i7, hex-core):

```
env OMP_NUM_THREADS=12 likwid-perfctr -g MEM -C N:0-11 ./a.out
```

# Using performance counters for diagnosing bad ccNUMA access locality



- Intel Westmere EP node (2x6 cores):

Only one memory BW per socket ("Uncore")

Metric	core 0	core 1	...	core 6	core 7	...
Runtime [s]	0.730168	0.733754		0.732808	0.732943	
CPI	10.4164	10.2654		10.5002	10.7641	
Memory bandwidth [MBytes/s]	11880.9	0	...	11732.4	0	...
Remote Read BW [MBytes/s]	<b>4219</b>	0		<b>4163.45</b>	0	
Remote Write BW [MBytes/s]	<b>1706.19</b>	0		<b>1705.09</b>	0	
Remote BW [MBytes/s]	<b><u>5925.19</u></b>	0		<b><u>5868.54</u></b>	0	



Half of BW comes from other socket!

# If all fails...



- Even if all placement rules have been carefully observed, you may still see nonlocal memory traffic. Reasons?
  - Program has erratic access patterns → may still achieve some access parallelism (see later)
  - OS has filled memory with buffer cache data:

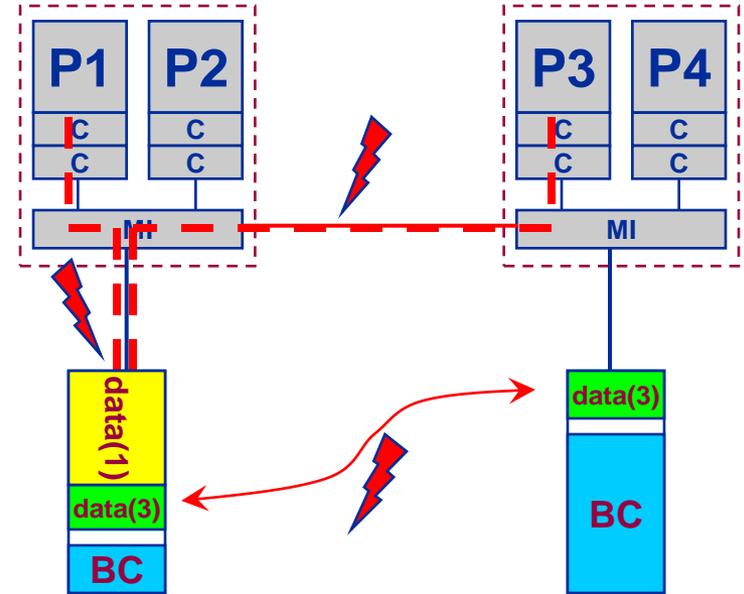
```
# numactl --hardware      # idle node!  
available: 2 nodes (0-1)  
node 0 size: 2047 MB  
node 0 free: 906 MB  
node 1 size: 1935 MB  
node 1 free: 1798 MB
```

```
top - 14:18:25 up 92 days, 6:07, 2 users, load average: 0.00, 0.02, 0.00  
Mem: 4065564k total, 1149400k used, 2716164k free, 43388k buffers  
Swap: 2104504k total, 2656k used, 2101848k free, 1038412k cached
```



- **OS uses part of main memory for disk buffer (FS) cache**

- If FS cache fills part of memory, apps will probably allocate from foreign domains
- → non-local access!
- “sync” is not sufficient to drop buffer cache blocks



- **Remedies**

- Drop FS cache pages after user job has run (admin’s job)
  - seems to be automatic after aprun has finished on Crays
- User can run “sweeper” code that allocates and touches all physical memory before starting the real application
- `numactl` tool or `aprun` can force local allocation (where applicable)
- Linux: There is no way to limit the buffer cache size in standard kernels



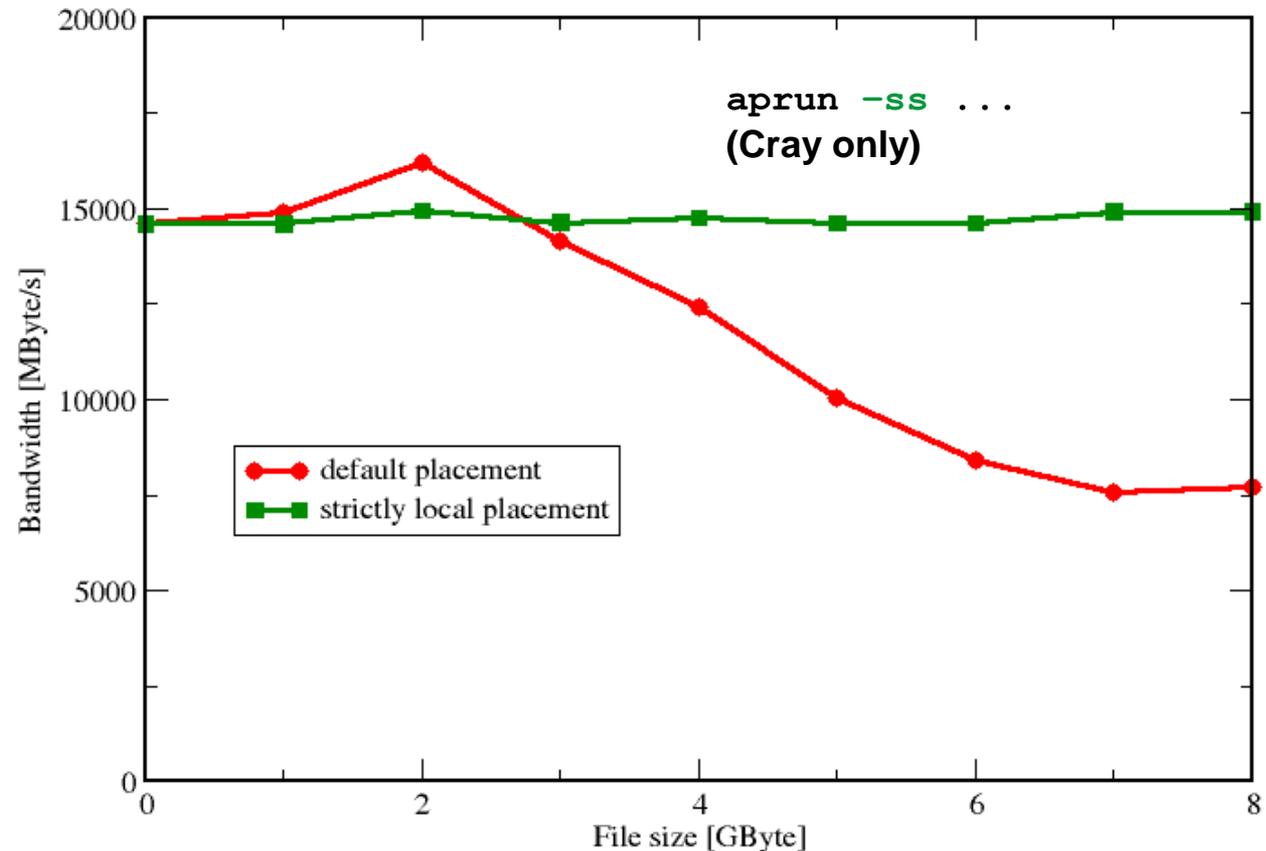
## Real-world example: ccNUMA and the Linux buffer cache

### Benchmark:

1. Write a file of some size from LD0 to disk
2. Perform bandwidth benchmark using all cores in LD0 and maximum memory installed in LD0

**Result: By default, Buffer cache is given priority over local page placement**

**→ restrict to local domain if possible!**





- Sometimes access patterns are just not nicely grouped into contiguous chunks:

```
double precision :: r, a(M)
!$OMP parallel do private(r)
do i=1,N
  call RANDOM_NUMBER(r)
  ind = int(r * M) + 1
  res(i) = res(i) + a(ind)
enddo
!OMP end parallel do
```

- Or you have to use tasking/dynamic scheduling:

```
!$OMP parallel
!$OMP single
do i=1,N
  call RANDOM_NUMBER(r)
  if(r.le.0.5d0) then
!$OMP task
    call do_work_with(p(i))
!$OMP end task
  endif
enddo
!$OMP end single
!$OMP end parallel
```

- In both cases page placement cannot easily be fixed for perfect parallel access



- **Worth a try: Interleave memory across ccNUMA domains to get at least some parallel access**

1. Explicit placement:

```
!$OMP parallel do schedule(static,512)  
do i=1,M  
  a(i) = ...  
enddo  
!$OMP end parallel do
```

Observe page alignment of array to get proper placement!

2. Using global control via `numactl`:

```
numactl --interleave=0-3 ./a.out
```

This is for **all** memory, not just the problematic arrays!

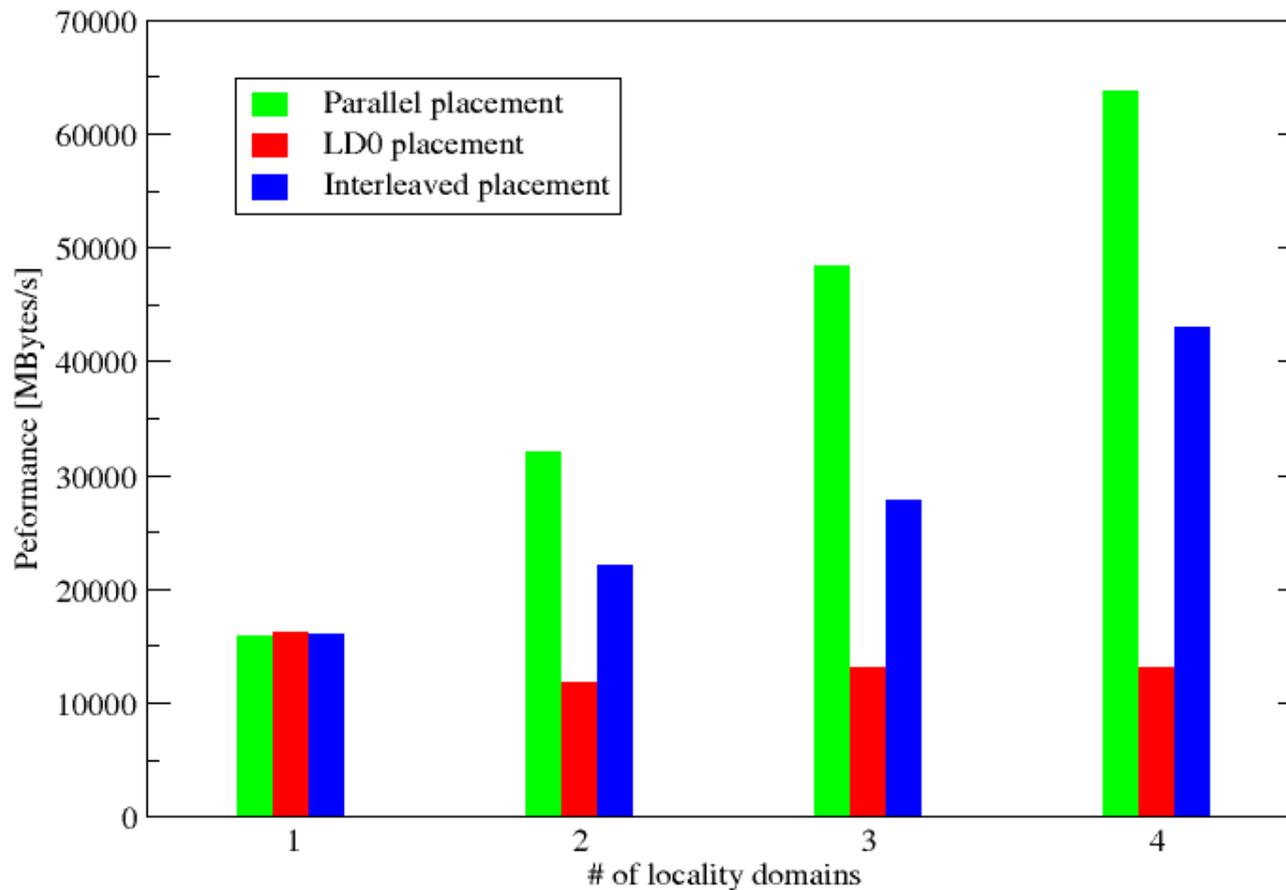
- **Fine-grained program-controlled placement via `libnuma` (Linux) using, e.g., `numa_alloc_interleaved_subset()`, `numa_alloc_interleaved()` and others**

# The curse and blessing of interleaved placement:

*OpenMP STREAM on a Cray XE6 Interlagos node*



- **Parallel init:** Correct parallel initialization
- **LD0:** Force data into LD0 via `numactl -m 0`
- **Interleaved:** `numactl --interleave <LD range>`

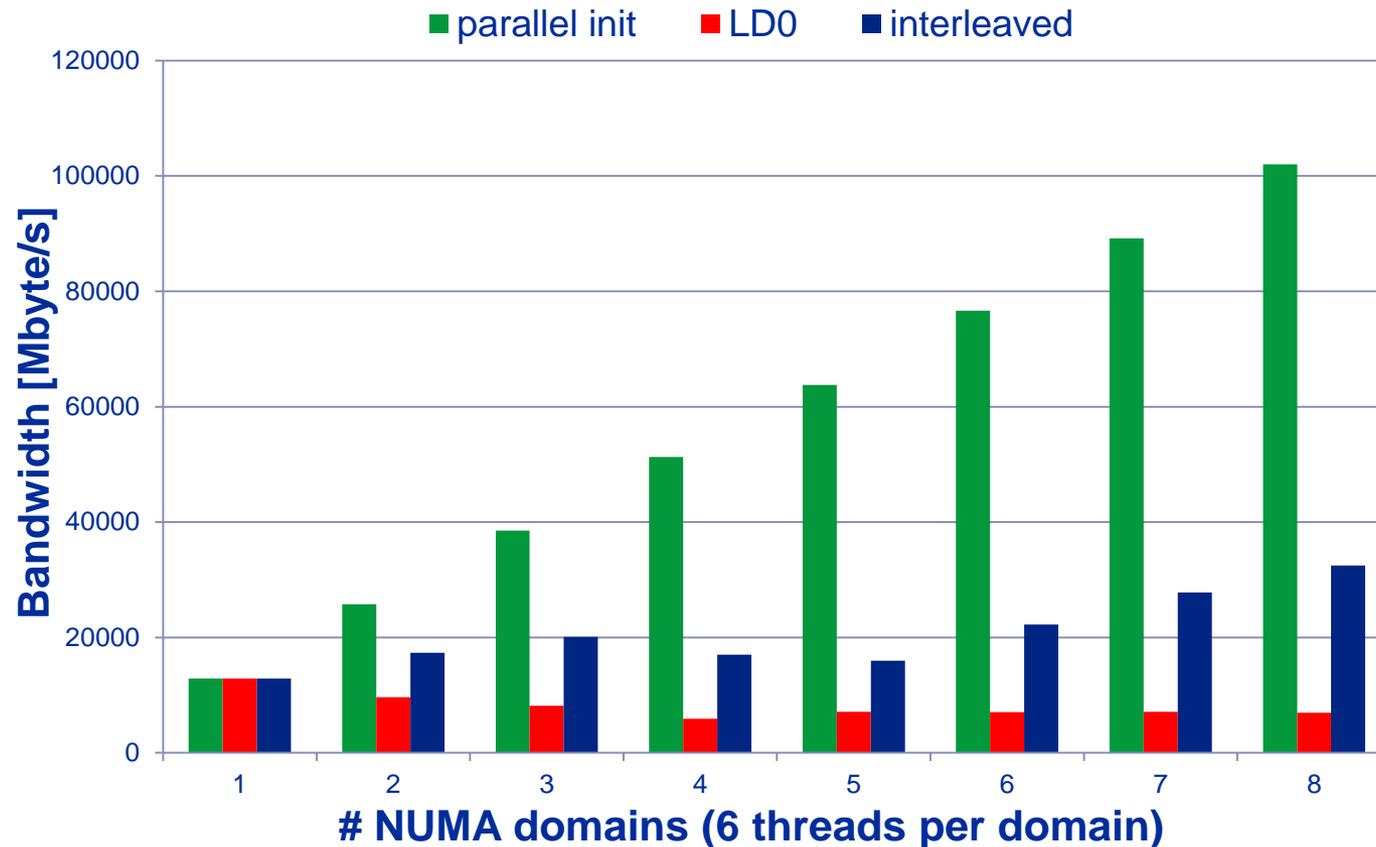


# The curse and blessing of interleaved placement:

*OpenMP STREAM triad on 4-socket (48 core) Magny Cours node*



- **Parallel init:** Correct parallel initialization
- **LD0:** Force data into LD0 via `numactl -m 0`
- **Interleaved:** `numactl --interleave <LD range>`





- **Identify the problem**
  - Is ccNUMA an issue in your code?
  - Simple test: run with `numactl --interleave`
- **Apply first-touch placement**
  - Look at initialization loops
  - Consider loop lengths and static scheduling
  - C++ and global/static objects may require special care
- **If dynamic scheduling cannot be avoided**
  - Consider round-robin placement
- **Buffer cache may impact proper placement**
  - Kick your admins
  - or apply sweeper code
  - If available, use runtime options to force local placement

---

# DEMO



- **Multicore architecture == multiple complexities**
  - Affinity matters → pinning/binding is essential
  - Bandwidth bottlenecks → inefficiency is often made on the chip level
  - Topology dependence of performance features → know your hardware!
- **Put cores to good use**
  - Bandwidth bottlenecks → surplus cores → functional parallelism!?
  - Shared caches → fast communication/synchronization → better implementations/algorithms?
- **Simple modeling techniques help us**
  - ... understand the limits of our code on the given hardware
  - ... identify optimization opportunities
  - ... learn more, especially when they do not work!
- **Simple tools get you 95% of the way**
  - e.g., LIKWID tool suite



Code:

```
double precision, dimension(100000000) :: a,b

do i=1,N
    s=s+a(i)*b(i)
enddo
```

**GPGPU:** 2880 cores,  $P_{\text{peak}} = 1.3 \text{ Tflop/s}$ ,  $b_S = 160 \text{ Gbyte/s}$

Optimal  
performance?

Moritz Kreutzer  
Markus Wittmann  
Thomas Zeiser  
Michael Meier



**THANK YOU.**



Bundesministerium  
für Bildung  
und Forschung

hpcADD  
FEPA  
SKALB

# Presenter Biographies



**Georg Hager** holds a PhD in computational physics from the University of Greifswald. He has been working with high performance systems since 1995, and is now a senior research scientist in the HPC group at Erlangen Regional Computing Center (RRZE). Recent research includes architecture-specific optimization for current microprocessors, performance modeling on processor and system levels, and the efficient use of hybrid parallel systems. See his blog at <http://blogs.fau.de/hager> for current activities, publications, and talks.



**Jan Treibig** holds a PhD in Computer Science from the University of Erlangen. He is now a postdoctoral researcher in the HPC Services group at Erlangen Regional Computing Center (RRZE). His current research revolves around architecture-specific and low-level optimization for current processor architectures, performance modeling on processor and system levels, and programming tools. He is the developer of LIKWID, a collection of lightweight performance tools. In his daily work he is involved in all aspects of user support in High Performance Computing: training, code parallelization, profiling and optimization, and the evaluation of novel computer architectures.



**Gerhard Wellein** holds a PhD in solid state physics from the University of Bayreuth and is a professor at the Department for Computer Science at the University of Erlangen. He leads the HPC group at Erlangen Regional Computing Center (RRZE) and has more than ten years of experience in teaching HPC techniques to students and scientists from computational science and engineering programs. His research interests include solving large sparse eigenvalue problems, novel parallelization approaches, performance modeling, and architecture-specific optimization.





## Books:

- G. Hager and G. Wellein: Introduction to High Performance Computing for Scientists and Engineers. CRC Computational Science Series, 2010. ISBN 978-1439811924

## Papers:

- M. Kreutzer, G. Hager, G. Wellein, H. Fehske, and A. R. Bishop: **A unified sparse matrix data format for modern processors with wide SIMD units**. Submitted. Preprint: [arXiv:1307.6209](https://arxiv.org/abs/1307.6209)
- G. Hager, J. Treibig, J. Habich and G. Wellein: **Exploring performance and power properties of modern multicore chips via simple machine models**. Submitted. Preprint: [arXiv:1208.2908](https://arxiv.org/abs/1208.2908)
- J. Treibig, G. Hager and G. Wellein: **Performance patterns and hardware metrics on modern multicore processors: Best practices for performance engineering**. Workshop on Productivity and Performance (PROPER 2012) at Euro-Par 2012, August 28, 2012, Rhodes Island, Greece. Preprint: [arXiv:1206.3738](https://arxiv.org/abs/1206.3738)
- M. Kreutzer, G. Hager, G. Wellein, H. Fehske, A. Basermann and A. R. Bishop: **Sparse Matrix-vector Multiplication on GPGPU Clusters: A New Storage Format and a Scalable Implementation**. Workshop on Large-Scale Parallel Processing 2012 (LSPP12), DOI: [10.1109/IPDPSW.2012.211](https://doi.org/10.1109/IPDPSW.2012.211)
- J. Treibig, G. Hager, H. Hofmann, J. Hornegger and G. Wellein: **Pushing the limits for medical image reconstruction on recent standard multicore processors**. International Journal of High Performance Computing Applications, (published online before print). DOI: [10.1177/1094342012442424](https://doi.org/10.1177/1094342012442424)



Papers continued:

- G. Wellein, G. Hager, T. Zeiser, M. Wittmann and H. Fehske: **Efficient temporal blocking for stencil computations by multicore-aware wavefront parallelization**. Proc. COMPSAC 2009.  
DOI: [10.1109/COMPSAC.2009.82](https://doi.org/10.1109/COMPSAC.2009.82)
- M. Wittmann, G. Hager, J. Treibig and G. Wellein: **Leveraging shared caches for parallel temporal blocking of stencil codes on multicore processors and clusters**. Parallel Processing Letters **20** (4), 359-376 (2010).  
DOI: [10.1142/S0129626410000296](https://doi.org/10.1142/S0129626410000296). Preprint: [arXiv:1006.3148](https://arxiv.org/abs/1006.3148)
- J. Treibig, G. Hager and G. Wellein: **LIKWID: A lightweight performance-oriented tool suite for x86 multicore environments**. Proc. PSTI2010, the First International Workshop on Parallel Software Tools and Tool Infrastructures, San Diego CA, September 13, 2010.  
DOI: [10.1109/ICPPW.2010.38](https://doi.org/10.1109/ICPPW.2010.38). Preprint: [arXiv:1004.4431](https://arxiv.org/abs/1004.4431)
- G. Schubert, H. Fehske, G. Hager, and G. Wellein: **Hybrid-parallel sparse matrix-vector multiplication with explicit communication overlap on current multicore-based systems**. Parallel Processing Letters 21(3), 339-358 (2011).  
DOI: [10.1142/S0129626411000254](https://doi.org/10.1142/S0129626411000254)
- J. Treibig, G. Wellein and G. Hager: **Efficient multicore-aware parallelization strategies for iterative stencil computations**. Journal of Computational Science 2 (2), 130-137 (2011).  
DOI [10.1016/j.jocs.2011.01.010](https://doi.org/10.1016/j.jocs.2011.01.010)



Papers continued:

- J. Habich, T. Zeiser, G. Hager and G. Wellein: Performance analysis and optimization strategies for a D3Q19 Lattice Boltzmann Kernel on nVIDIA GPUs using CUDA. Advances in Engineering Software and Computers & Structures 42 (5), 266–272 (2011). DOI: [10.1016/j.advengsoft.2010.10.007](https://doi.org/10.1016/j.advengsoft.2010.10.007)
- J. Treibig, G. Hager and G. Wellein: Multicore architectures: Complexities of performance prediction for Bandwidth-Limited Loop Kernels on Multi-Core Architectures. DOI: [10.1007/978-3-642-13872-0\\_1](https://doi.org/10.1007/978-3-642-13872-0_1), Preprint: [arXiv:0910.4865](https://arxiv.org/abs/0910.4865).
- G. Hager, G. Jost, and R. Rabenseifner: Communication Characteristics and Hybrid MPI/OpenMP Parallel Programming on Clusters of Multi-core SMP Nodes. In: Proceedings of the Cray Users Group Conference 2009 (CUG 2009), Atlanta, GA, USA, May 4-7, 2009. [PDF](#)
- R. Rabenseifner and G. Wellein: Communication and Optimization Aspects of Parallel Programming Models on Hybrid Architectures. International Journal of High Performance Computing Applications 17, 49-62, February 2003. DOI: [10.1177/1094342003017001005](https://doi.org/10.1177/1094342003017001005)

# HPC textbook

*Georg Hager and Gerhard Wellein:*

## **Introduction to High Performance Computing for Scientists and Engineers**

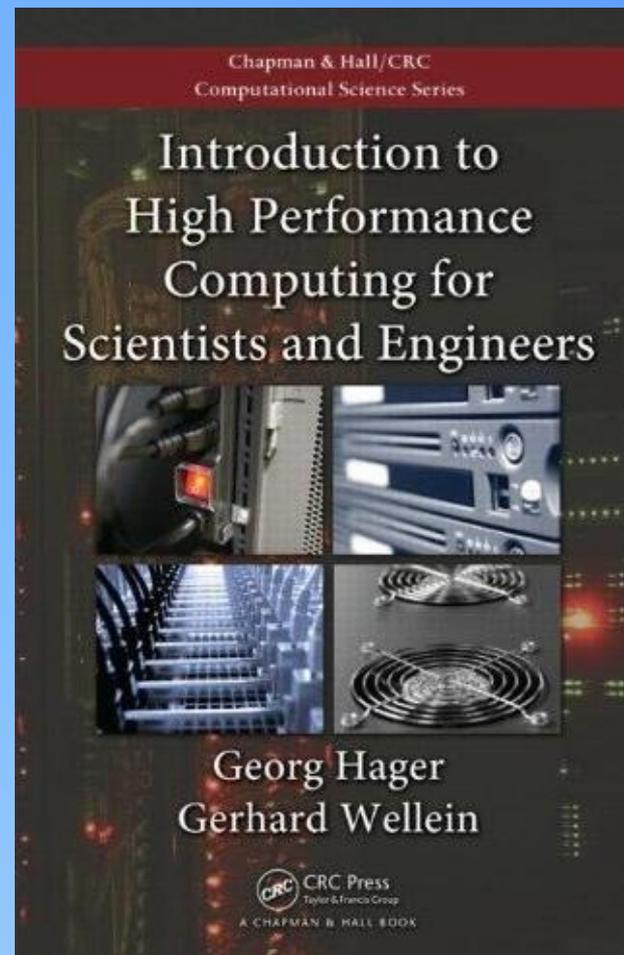
CRC Press, ISBN 978-1439811924

356 pages

July 2010

"Georg Hager and Gerhard Wellein have developed a very approachable introduction to high performance computing for scientists and engineers. Their style and descriptions are easy to read and follow. ... This book presents a balanced treatment of the theory, technology, architecture, and software for modern high performance computers and the use of high performance computing systems. The focus on scientific and engineering problems makes it both educational and unique. I highly recommend this timely book for scientists and engineers. I believe it will benefit many readers and provide a fine reference."

— *From the Foreword by Jack Dongarra, University of Tennessee, Knoxville, USA*



*Georg Hager & Gerhard Wellein:*

## **Introduction to High Performance Computing for Scientists and Engineers**

- Covers **basic sequential optimization strategies** and the dominating parallelization paradigms, including shared-memory parallelization with **OpenMP** and distributed-memory parallel programming with **MPI**
- Highlights the importance of **performance modeling** of applications on all levels of a system's architecture
- Contains numerous **case studies** drawn from the authors' invaluable experiences in HPC user support, performance optimization, and benchmarking
- Explores important contemporary concepts, such as **multicore** architecture and **affinity issues**
- Includes code examples in **Fortran** and, if relevant, C and **C++**
- Provides end-of-chapter **exercises with solutions** in an appendix
- <http://www.hpc.rrze.uni-erlangen.de/HPC4SE/>



# Introduction to High Performance Computing for Scientists and Engineers

## *Contents*

- **Modern Processors**
  - Stored-program computer architecture
  - General-purpose cache-based microprocessor architecture
  - Memory hierarchies
  - Multicore processors
  - Multithreaded processors
  - Vector processors
- **Basic Optimization Techniques for Serial Code**
  - Scalar profiling
  - Common sense optimizations
  - Simple measures, large impact
  - The role of compilers
  - C++ optimizations
- **Data Access Optimization**
  - Balance analysis and lightspeed estimates
  - Storage order
  - Case study: The Jacobi algorithm
  - Case study: Dense matrix transpose
  - Algorithm classification and access optimizations
  - Case study: Sparse matrix-vector multiply
- **Parallel Computers**
  - Taxonomy of parallel computing paradigms
  - Shared-memory computers
  - Distributed-memory computers
  - Hierarchical (hybrid) systems
  - Networks
- **Basics of Parallelization**
  - Why parallelize?
  - Parallelism
  - Parallel scalability
- **Shared-Memory Parallel Programming with OpenMP**
  - Short introduction to OpenMP
  - Case study: OpenMP-parallel Jacobi algorithm
  - Advanced OpenMP: Wavefront parallelization
- **Efficient OpenMP Programming**
  - Profiling OpenMP programs
  - Performance pitfalls
  - Case study: Parallel sparse matrix-vector multiply

# Introduction to High Performance Computing for Scientists and Engineers

## *Contents continued*

- **Locality Optimizations on ccNUMA Architectures**
  - Locality of access on ccNUMA
  - Case study: ccNUMA optimization of sparse MVM
  - Placement pitfalls
  - ccNUMA issues with C++
- **Distributed-Memory Parallel Programming with MPI**
  - Message passing
  - A short introduction to MPI
  - Example: MPI parallelization of a Jacobi solver
- **Efficient MPI Programming**
  - MPI performance tools
  - Communication parameters
  - Synchronization, serialization, contention
  - Reducing communication overhead
  - Understanding intranode point-to-point communication
- **Hybrid Parallelization with MPI and OpenMP**
  - Basic MPI/OpenMP programming models
  - MPI taxonomy of thread interoperability
  - Hybrid decomposition and mapping
  - Potential benefits and drawbacks of hybrid programming
- **Appendix A: Topology and Affinity in Multicore Environments**
- **Appendix B: Solutions to the Problems**
- **Bibliography**
- **Index**