



# Part I: Introduction to compute node architecture

General Concept

Single Core: Pipelining, Superscalarity, SMT, SIMD

Memory hierarchy and Data Transfers

GPU vs. CPU



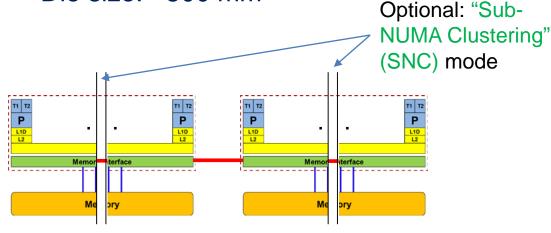
#### Multi-core today: Intel Xeon Skylake SP (2017)

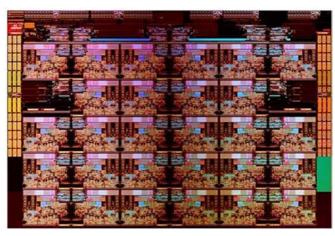


- Xeon "Skylake SP" (Platinum/Gold/Silver/Bronze):
   Up to 28 cores running at 2+ GHz (+ "Turbo Mode": 3.8+ GHz)
  - Reincarnated as "Cascade Lake" in 2018

- Simultaneous Multithreading (SMT)
   → reports as 56-way chip
- 8 Billion Transistors / 14 nm

Die size: ~500 mm²





VikiChi

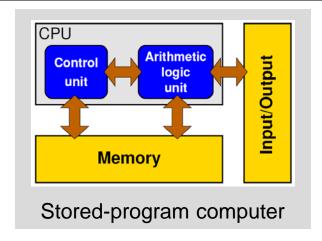
2015: Broadwell architecture

- Cluster on Die (analogous to SNC)
- Up to 24 cores

2-socket server

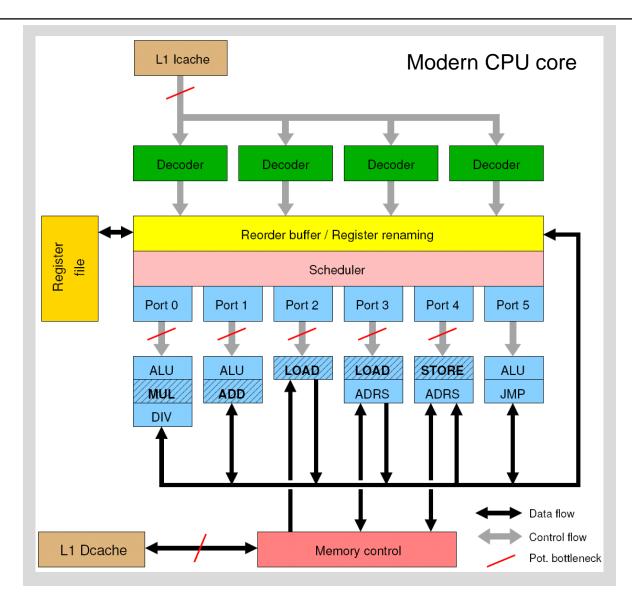
#### General-purpose cache based microprocessor core





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

The clock cycle is the "heartbeat" of the core

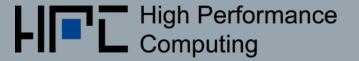






# Part I: Introduction to compute node architecture

Single core: Pipelining, Superscalarity, SMT, SIMD



#### Pipelining of arithmetic/functional units



#### Idea:

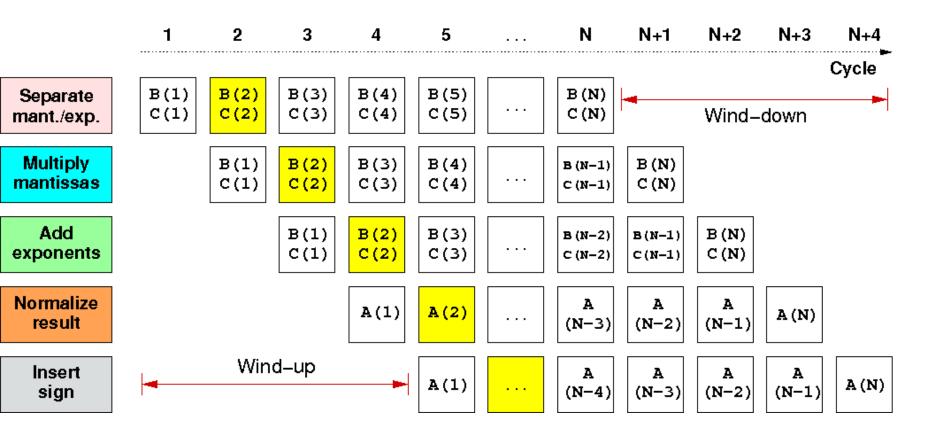
- Split complex instruction into several simple / fast steps (stages)
- Each step takes the same time, e.g., one cycle
- Execute different steps on different instructions at the same time (in parallel)
- Allows for shorter cycle times (simpler logic circuits), e.g.:
  - floating point multiplication 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 sufficient # of independent instructions required
- Requires complex instruction scheduling by compiler/hardware
  - software-pipelining / out-of-order execution
- Pipelining is widely used in modern computer architectures

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



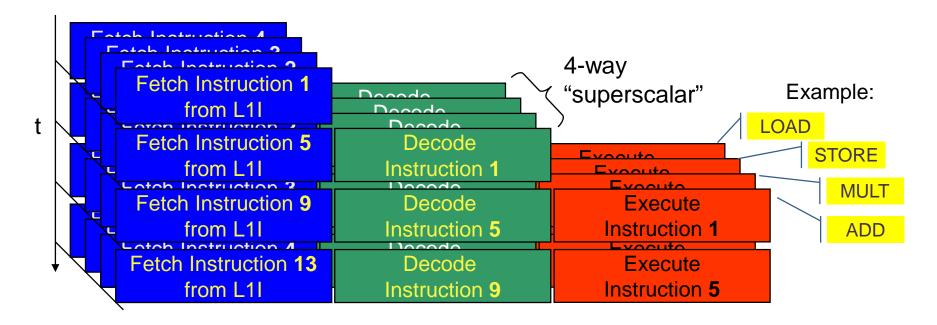


First result is available after 5 cycles (=latency of pipeline)! Wind-up/-down phases: Empty pipeline stages

#### Superscalar Processors – Instruction Level Parallelism

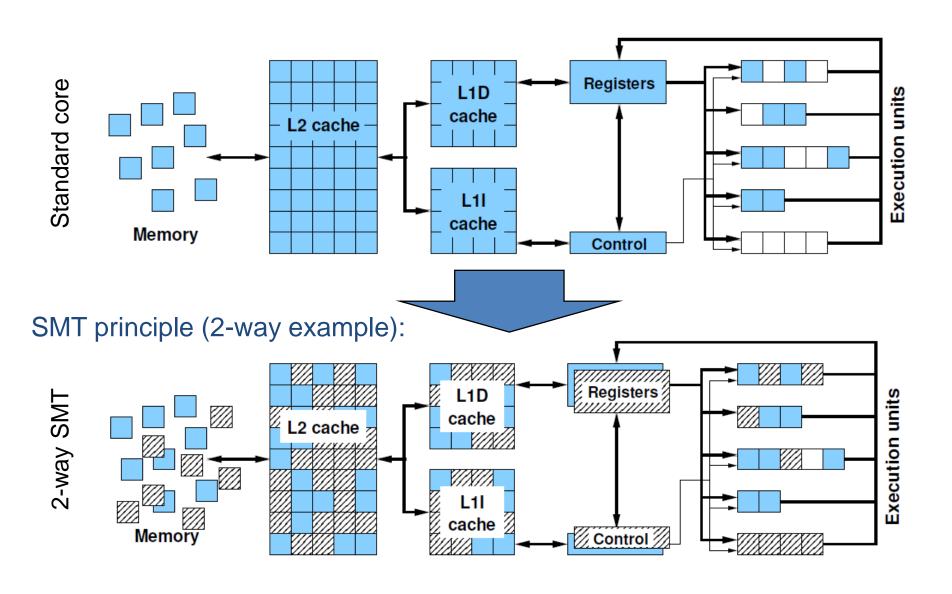


- Multiple units enable use of Instruction Level Parallelism (ILP): Instruction stream is "parallelized" on the fly
- Instructions from different loop iterations retired at the same time



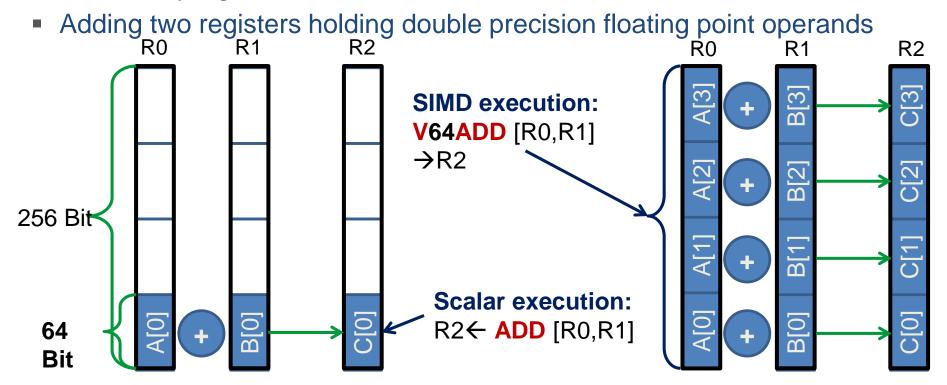
- Issuing m concurrent instructions per cycle: m-way superscalar
- Modern processors are 4- to 6-way superscalar & can perform 2 floating-point instructions per cycle





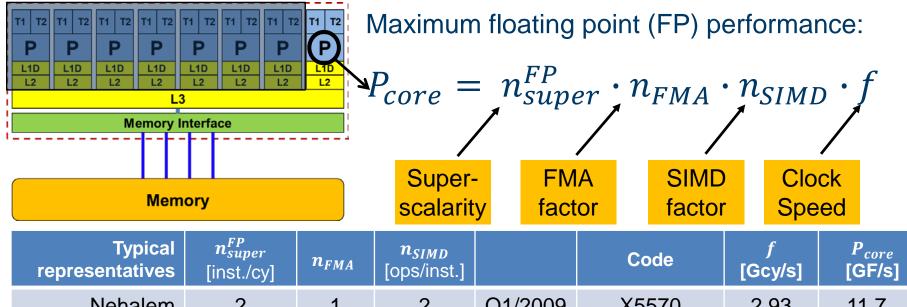


- Single Instruction Multiple Data (SIMD) operations allow the concurrent execution of the same operation on "wide" registers
- x86 SIMD instruction sets:
  - SSE: register width = 128 Bit  $\rightarrow$  2 double precision floating point operands
  - AVX(/2): register width = 256 Bit  $\rightarrow$  4 double precision floating point operands
  - AXV512: you get it.



#### There is no single driving force for single core performance!





Typical representatives	$n_{super}^{rr}$ [inst./cy]	$n_{FMA}$	n <sub>SIMD</sub> [ops/inst.]		Code	f [Gcy/s]	P <sub>core</sub> [GF/s]
Nehalem	2	1	2	Q1/2009	X5570	2.93	11.7
Sandy Bridge	2	1	4	Q1/2012	E5-2680	2.7	21.6
Haswell	2	2	4	Q3/2014	E5-2695 v3	2.3	36.8
Broadwell	2	2	4	Q1/2016	E5-2699 v4	2.2	35.2
Skylake	2	2	8	Q3/2017	Gold 6148	2.4	76.8
AMD Zen	2	2	2	Q1/2017	Epyc 7451	2.3	18.4
AMD Zen2	2	2	4	Q3/2019	Epyc 7742	2.25	36.0
Fujitsu A64FX	2	2	8	Q2/2020	FX700	1.8	57.6
IBM POWER8	2	2	2	Q2/2014	S822LC	2.93	23.4

### A "simple" example: The sum reduction



...In single precision (32 Bit) on an AVX-capable core (ADD latency = 3 cy)

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

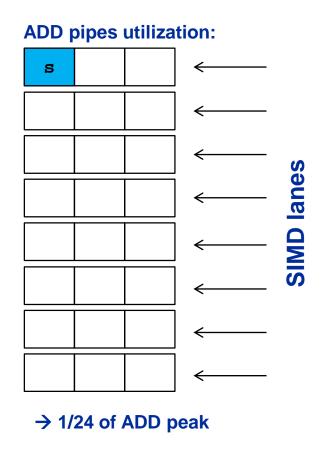
- Loop-carried dependency on summation variable
- Execution stalls at every ADD until previous ADD is complete
- → No pipelining?
- → No SIMD?



### Plain scalar code, no SIMD

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

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



#### Applicable peak for the sum reduction (II)



```
Scalar code, 3-way "modulo variable expansion"
```

LOAD r1.0 
$$\leftarrow$$
 0  
LOAD r2.0  $\leftarrow$  0  
LOAD r3.0  $\leftarrow$  0  
i  $\leftarrow$  1

LOAD r4.0 
$$\leftarrow$$
 a(i)  
LOAD r5.0  $\leftarrow$  a(i+1)

LOAD r6.0 
$$\leftarrow$$
 a(i+2)

$$i+=3 \rightarrow ? loop$$

do $i = 1, N, 3$				
s1 = s1 + a(i+0)				
s2 = s2 + a(i+1)				
s3 = s3 + a(i+2)				
enddo				
s = s + s1+s2+s3				

s1	s2	<b>s</b> 3

→ 1/8 of ADD peak

#### Applicable peak for the sum reduction (III)



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

```
LOAD [r1.0,...,r1.7] \leftarrow [0,...,0]

LOAD [r2.0,...,r2.7] \leftarrow [0,...,0]

LOAD [r3.0,...,r3.7] \leftarrow [0,...,0]

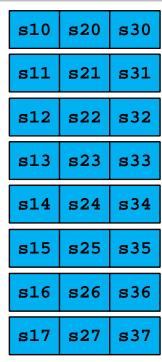
i \leftarrow 1
```

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

#### loop:

```
LOAD [r4.0,...,r4.7] \leftarrow [a(i),...,a(i+7)] # SIMD LOAD LOAD [r5.0,...,r5.7] \leftarrow [a(i+8),...,a(i+15)] # SIMD LOAD [r6.0,...,r6.7] \leftarrow [a(i+16),...,a(i+23)] # SIMD ADD [r6.0,...,r6.7] \leftarrow [a(i+16),...,a(i+23)] # SIMD ADD [r6.0,...,r6.7] \leftarrow [a(i+16),...,a(i+23)] # SIMD ADD [r6.0,...,r6.7] \leftarrow [a(i+16),...,a(i+23)]
```

```
ADD r1 \leftarrow r1 + r4 # SIMD ADD
ADD r2 \leftarrow r2 + r5 # SIMD ADD
ADD r3 \leftarrow r3 + r6 # SIMD ADD
```



#### Sum reduction



#### **Questions**

- When can this performance actually be achieved?
  - No data transfer bottlenecks
  - No other in-core bottlenecks
    - Need to execute (3 LOADs + 3 ADDs + 1 increment + 1 compare + 1 branch) in 3 cycles
- What does the compiler do?
  - If allowed and capable, the compiler will do this automatically
- Is the compiler allowed to do this at all?
  - Not according to language standards
  - High optimization levels can violate language standards
- What about the "accuracy" of the result?
  - Good question ;-)





## Part I: Introduction to compute node architecture

Memory Hierarchy and Data Transfers

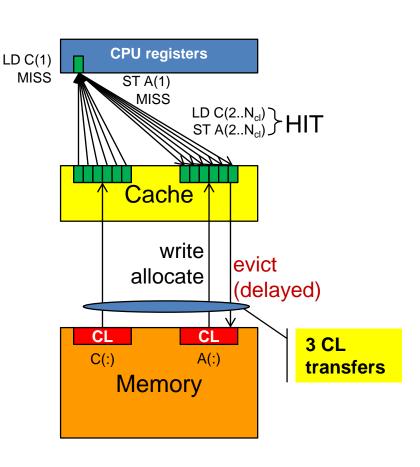


# Registers and caches: Data transfers in a memory hierarchy



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

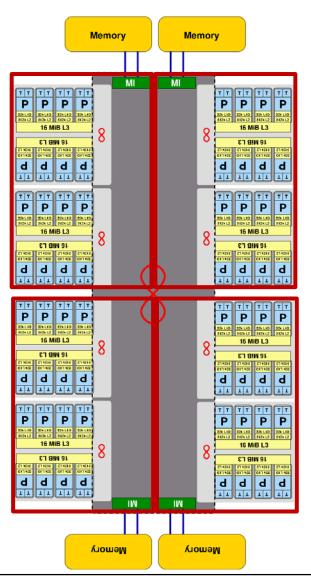
- Remember: Caches are organized in cache lines (e.g., 64 bytes)
- Only complete cache lines are transferred between memory hierarchy levels (except L1 ←→registers)
- Cache MISS: Load or store instruction does not find the data in a cache level
   → CL transfer required
- Example: Array copy A(:)=C(:)
- "Store miss" → write allocate (WA)
- Techniques exists to avoid WA



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



#### Processor "Chip" (Socket)



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





## Part I: Introduction to compute node architecture

GPU vs CPU



### Nvidia A100 "Ampere" SXM4 specs



#### **Architecture**

- 54.2 B Transistors
- ~ 1.4 GHz clock speed
- ~ 108 "SM" units
  - 64 SP "cores" each (FMA)
  - 32 DP "cores" each (FMA)
  - 4 "Tensor Cores" each
  - 2:1 SP:DP performance
- 9.7 TFlop/s DP peak (FP64)
- 40 MiB L2 Cache
- 40 GB (5120-bit) HBM2
- MemBW ~ 1555 GB/s (theoretical)
- MemBW ~ 1400 GB/s (measured)



© Nvidia

$$P_{peak}^{DP} = n_{SM} \cdot n_{core} \cdot n_{FP} \cdot f$$
# SMs # CUDA # FP ops/cy

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

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



GPU vs. CPU light speed estimate (per processor chip)

Cache

DRAM

CPU

ALU

ALU

Control

DRAM

MemBW  $\sim 7 - 10x$ 

Peak  $\sim 4-8x$ 

	2 x AMD EPYC 7742 "Rome"	NVidia Tesla A100 "Ampere"	
Cores@Clock	2 x 64 @ 2.25 GHz	108 SMs @ ~1.4 GHz	
FP32 Performance/core	72 GFlop/s	~179 GFlop/s	
Threads@STREAM	~16	> 100000	
FP32 peak	9.2 TFlop/s	~19.5 TFlop/s	
Stream BW (meas.)	2 x 190 GB/s	1400 GB/s	
Transistors / TDP	~2x40 Billion / 2x225 W	54 Billion/400 W	

#### Conclusions about architecture



- 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: 4-64) to massive (GPGPU: 10's-100'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

#### Note:

- Performance features are largely independent of the programming model
- But programming models are sensitive to architecture
  - Topology/affinity influences overheads
  - Standards do not contain (many) topology-aware features