



Some details on Modern Architecture

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Some details on Modern Architectures

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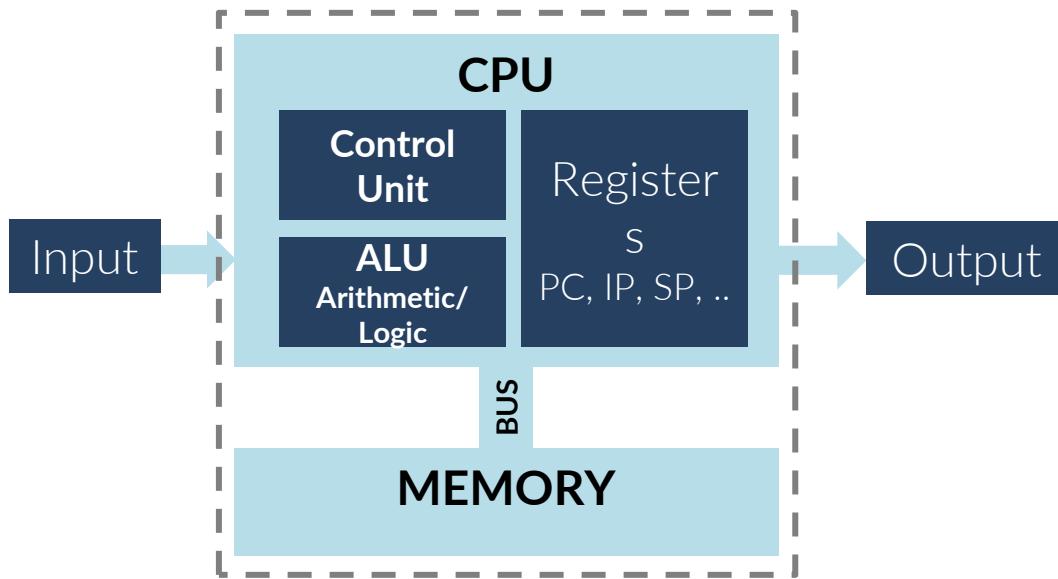
This lecture presents, *in very condensed way*, the fundamental traits of the **single-core** modern architecture, in their historical developments and roots.

The aim is to convince you that knowing it is important in order to write efficient codes.



Once upon a time..

The computer architecture was much simpler than today.
Well, if you really think that the wonderful abstraction
known as Von Neumann architecture, which brought order
into chaos, is “simple”

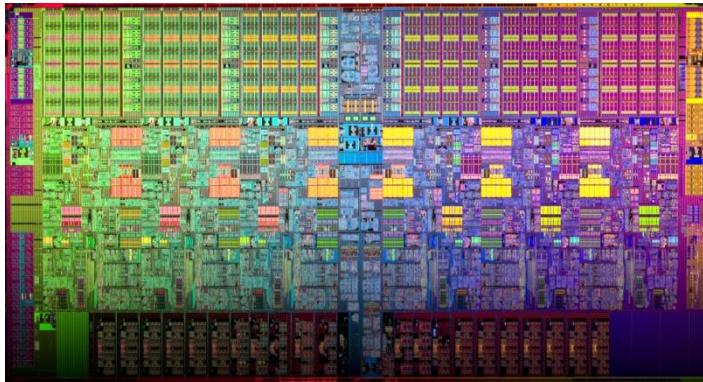


In the **Von Neumann architecture** (still taught as the fundamental model)

- **there is only 1 processing unit**
- **1 instructions is executed at a time**
- **memory is “flat”:**
 - access on any location has always the same cost
 - access to memory has the same cost than op execution



While today...



NOT an extreme example: 6-cores Intel Xeon e5600

(*) “cost” is in terms of the CPU-cycles currency

- there are *many* processing units
- many instructions can be executed at a time
- many data can be processed at a time
- “instructions” are internally broken down in many simpler μ ops that are pipelined
 - different instructions could have quite different^(*) cost
- memory is strongly not “flat”:
 - there is a strong memory hierarchy
 - access memory can have very different costs^(*) depending on the location
 - accessing RAM is way more costly than performing a μ op or reading an internal register

In the next slides we'll go through all this features in chronological order, as they developed in time



Look back in time

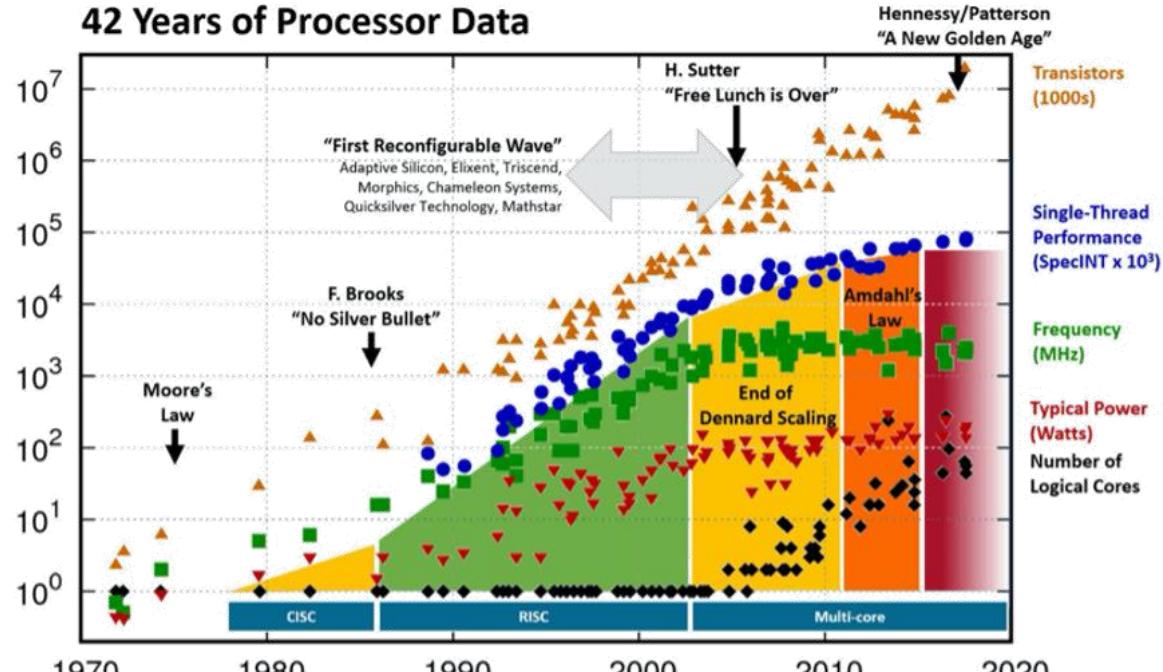
The so-called “Moore’s law” has been there since more than 50 years:
every 18 months the number of transistor per unit area doubles (*), at the same manufacturing cost.

meaning that every 18 months you could buy a commodity CPUs with 2x logics than the previous generation, at the same cost.

Basically that means more complex circuits, and enhanced capabilities and *higher frequencies*: all together, the code execution was faster.
That has been called the “free lunch era”.

However, every growth comes to an end, especially the exponential ones.

(*Note: there have been even faster growths in other fields, for instance in data storage density.

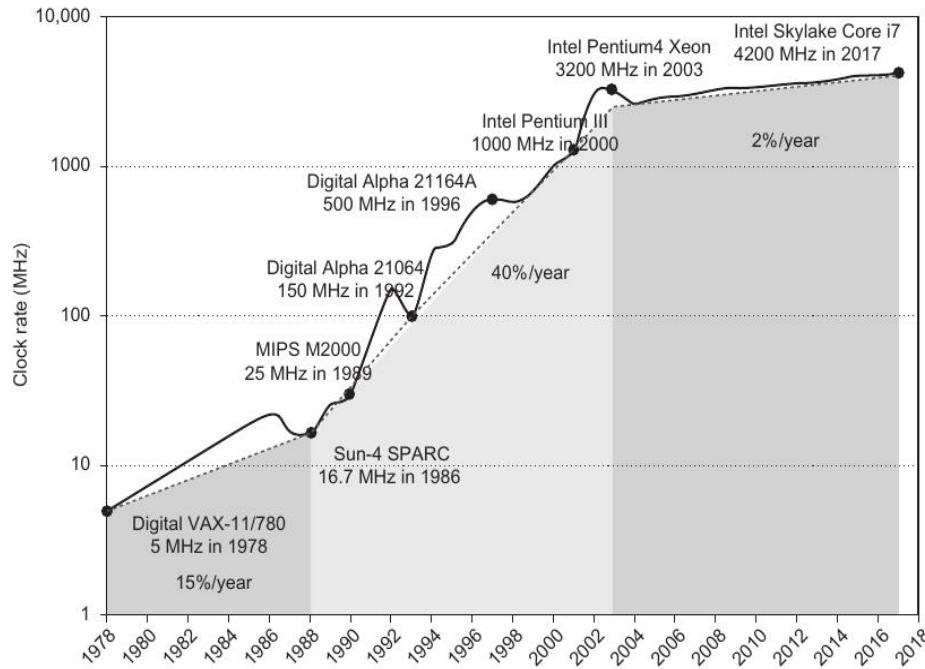


Hennessy and Patterson, Turing Lecture 2018, overlaid over “42 Years of Processors Data”

<https://www.karlrupp.net/2018/02/42-years-of-microprocessor-trend-data/>; “First Wave” added by Les Wilson, Frank Schirrmeyer
Original data up to the year 2010 collected and plotted by M. Horowitz, F. Labonte, O. Shacham, K. Olukotun, L. Hammond, and C. Batten
New plot and data collected for 2010-2017 by K. Rupp



Increase of clock frequency



The power required per transistor is
 $C \times V^2 \times f$

Roughly the capacitance and the voltage of transistor shrinks with the feature size, whereas the scaling is much more complicated for the wires.

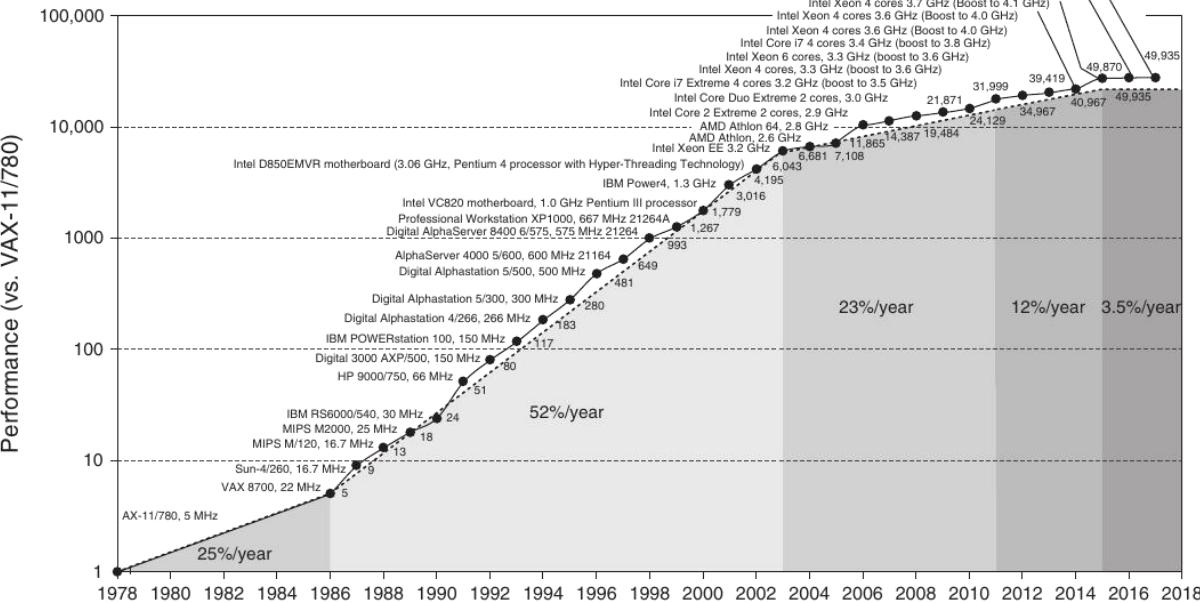
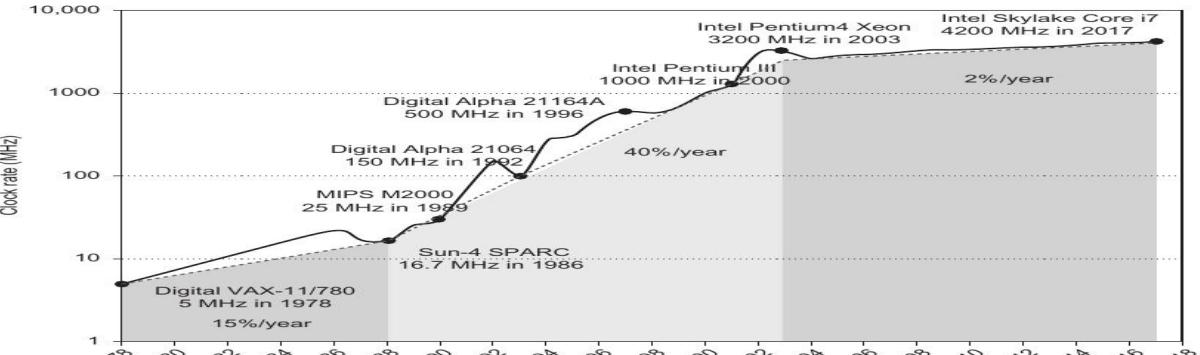
That is basically addressed as the breaking of the Dennard's scaling.

Overall, a typical CPU got from ~2W power to ~100W which is at the limit of the air cooling capacity.

From Hennessy & Patterson, Computer Architecture - A quantitative approach, 6th Ed, 2017

Relating the clock growth and the performance growth

(“performance” here is an indicator drawn from some standard arithmetic test)



From Hennessy & Patterson, Computer Architecture - A quantitative approach, 6th Ed, 2017

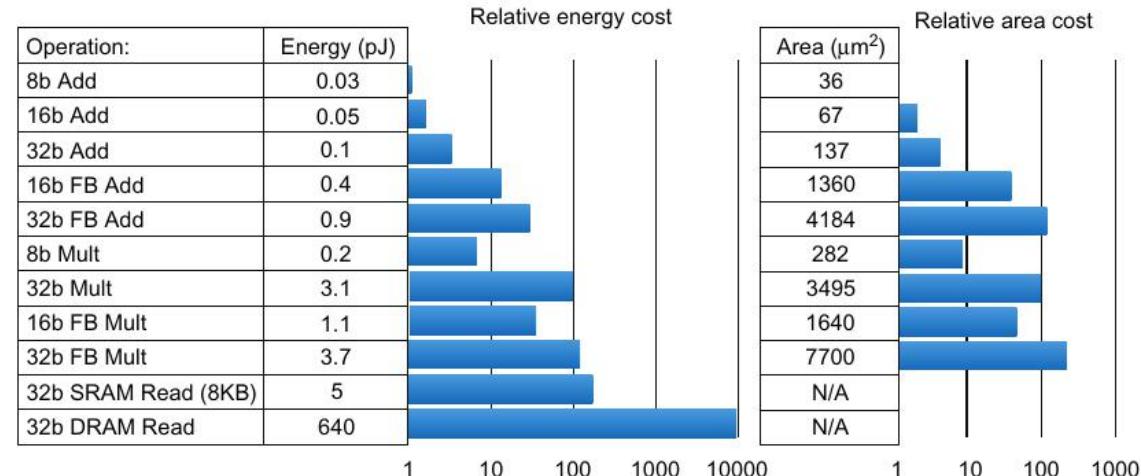


The energy and power are a major design issue

Primary strategies to cope with the power wall:

1. Turn off inactive circuits (*dark silicon*)
2. Dowscale Voltage and Frequency for both cores and DRAM
3. Thermal Power Design, or design for typical case
4. Overclocking for a short period of time and possibly for just a fraction of the chip

Static power, $P_{\text{static}} \propto \text{Current}_{\text{static}} \times V$, is also an important factor in the power consumption. It increases with the number of transistor while the current leakage increases as the feature size decreases and could amount to ~25% of the total power consumption.



Energy numbers are from Mark Horowitz *Computing's Energy problem (and what we can do about it)*. ISSCC 2014
Area numbers are from synthesized result using Design compiler under TSMC 45nm tech node. FP units used DesignWare Library.

From Hennessy & Patterson, Computer Architecture - A quantitative approach, 6th Ed, 2017



The “free lunch”

During a couple of decades, we have relied on the Moore's law and on the Dennard's scaling to have

- 1) more *capable* CPUs
- 2) faster CPUs (increasing the frequency, the CPU can execute the same ops at a faster pace)

The burden of performance was basically on the hardware side.

Then, something happened.



The breaking of Dennard's scaling



The **Dennard's scaling** explained to physicists:

Dennard (1974) described **constant-field scaling**. If you **shrink every linear dimension by a factor $\kappa > 1$** (so new length $L' = L/\kappa$) and also scale supply and threshold voltages by $1/\kappa$, while upping doping appropriately, then:

- Electric fields stay roughly constant (since $E \sim V/L$ and both scale by $1/\kappa$).
- Capacitance per gate scales like $C \propto \epsilon A/t \sim 1/\kappa$.
- Delay scales down ($\tau \sim RC \propto 1/\kappa$), so **frequency goes up** ($f \propto \kappa$).
- Dynamic power per gate $P_{\text{dyn}} \sim CV^2f \propto (1/\kappa)(1/\kappa^2)(\kappa) = 1/\kappa^2$.
- Transistor density rises as κ^2 .
Multiplying density by per-gate power gives **power density \approx constant**.

In a motto: **smaller & faster at constant heat.**



The breaking of Dennard's scaling



In a motto: **smaller & faster at constant heat.**

Wow.



The breaking of Dennard's scaling



Why Dennard's scaling broke in the mid of 2000s

1. Voltage stopped scaling.

You can't keep dropping V_{DD} once V_T (threshold) stops tracking it. The subthreshold slope at room temp bottoms near ~60 mV/dec for an ideal MOSFET; pushing V_T lower blows up subthreshold leakage. With V_{DD} stuck ~1 V, the key energy term CV^2 ceased shrinking.

2. Leakage currents exploded.

As channels thinned and oxides approached a few atomic layers, you got gate tunneling, stronger DIBL (drain-induced barrier lowering), and overall exponential leakage growth. Dynamic power stopped being the only game; static power became a first-order term.

3. Velocity saturation and mobility limits.

At nanometer fields, carriers hit velocity-saturation; you don't get the ideal $1/\kappa$ delay.

4. Interconnect became a bottleneck.

Wires didn't follow device scaling: RC delays worsened as cross-sections shrank; resistivity effectively increases with surface/grain-boundary scattering. Moving charge across the chip became slower and costlier than switching a gate.

5. Thermal reality.

With V pinned but clocks still rising, **power density** rose. That's the **power wall**: chips could no more dissipate the heat, and would have melt at increased frequencies.



The impact of the **End of Dennard's scaling**.

A. Frequency plateau

Stuck at ~2GHz since ~20yrs (the so called “*boost frequency*” works for a limited time and for a subset of cores).

B. Multi-core

If you can't push further a single one, put many at work.

→ multi-core → wider vector registers → heterogeneous-cores (GPUs/FPGAs/Vector)

C. Device innovations.

In *Geometry* (non-planer, 3D stacking, HBM, to reduce the joule/bit) and *doping*

D. ALGORITHMIC LEVEL

Lots of things. That is exactly the scope of this course.

→ the burden of performance has been significantly moved to the programmers' shoulders



50s - 70s	80s - 90s	90s - 2000s	mid 2000s	last 20yrs	next
<ul style="list-style-type: none">Architectures were “simple”Memory performance was close to cpuFrequency increase was driving the performance gain	<p>The larger number of transistors/cm² permitted more sophisticated logics:</p> <ul style="list-style-type: none">Superscalarity → many functional units executing in a clockout-of-order execution (<i>hint: Tomasulo's algorithm</i>)ILP starts to be power-hungry	<p>The epoch of MEMORY WALL.</p> <p>The CPU ops beats DRAM latency by orders of magnitude.</p> <p><i>Note: DRAM GHz buy you bandwidth, the latency is still a problem</i></p> <ul style="list-style-type: none">Deep cache hierarchyTLBsHW prefetchersbranch predictorsSIMD	<p>The epoch of POWER WALL and MULTICORE.</p> <p>Many simpler cores instead of a unique monster.</p> <p>TLP brings in issues:</p> <ul style="list-style-type: none">cache coherencymemory modelsNUMA	<p>The Cambrian epoch.</p> <ul style="list-style-type: none">More and wider vectors!Heterogeneous devices, and Massively parallel devices (GPUs, TPUs)SIMD on CPUs, SIMD on GPUsHBM, high-speed interconnects (NVlink, Infinity...), DPUs	<p>Who knows ?</p> <ul style="list-style-type: none">Proximity computation (compute near data / in memory: Neuromorphic devices?)domain-specific devices and ISA ?... ?



A small vocabulary

Functional Units	A hardware block inside a CPU core that executes a specific class of operations—e.g., INT/FP math, mem load/store ops, branch for control flow, vector/SIMD for lane-wise ops	NUMA	Non-Uniform Memory Access <i>we'll see in detail</i>
out-of-order execution	A CPU strategy that lets micro-ops run as soon as their inputs are ready, instead of strictly following the original program order	cache coherency	How you propagate changes in the content of variables among the caches of different cores
ILP / TLP	Instruction / Thread Level Parallelism	vector registers	Wide CPU Registers that can operate in chunks, performing the same op on all the chunks
Cache, TLB, Pipelines	<i>we'll see in the next slides</i>	HBM	High-Bandwidth Memory; very expensive RAM built to deliver high bandwidth at the cost of larger latencies
Prefetcher	The logic that fetches data and instructions from DRAM before their usage, based on predictions	NVlink	A custom NVIDIA's hardware connection to/among GPUs both on the motherboard and btw nodes
SIMD / SIMD	Single Instructions Multiple Data/Threads	Infinity Fabric	A high-speed (~100Gb per lane) interconnect among nodes
Branch Predictor	The logic that heuristically predicts whether a conditional will evaluate either true or false <i>we'll see in the next slides</i>	Neuromorphic	<i>I could not fit it here; experimental, qualitatively radically different approach to computation.</i>



At a glance

CPUs become faster than memory

Accessing the central DRAM becomes a major bottleneck due to a much larger latency than CPU. If the memory access is not carefully designed the CPU just waits for the data most of the time (*data starvation*).

A **memory hierarchy** is introduced to reduce the impact of this gap, and that introduces the key concept of **data locality**.

CPUs become super-scalar and acquire out-of-order capabilities

A modern core has more than one functional unit that can perform a class of operations (Arithmetic-logic, memory access, I/O, ...). That means that more than one operation can be performed in the same clock, if the code is suited to allow that, which is referred as **Instruction-Level-Parallelism** (ILP).

Operations are broken down into smaller stages and pipelined

The expected throughput is larger, at the condition that the **pipelines** are always as full as possible and do not stall due to data and control hazards (we'll see that later)

Branch predictors are an important part of the front-end

Branches play a major role in causing stalls in the pipelines and in the execution flow. Dealing with this is a key factor to increase the code's performance.

CPUs acquire vector capabilities

Special registers in the CPU have the capacity of performing the same operation on multiple data (**SIMD** - Same Instruction Multiple Data). That is referred as Data-Level-Parallelism. Not all the loops are vectorizable, that depends on a number of factors.

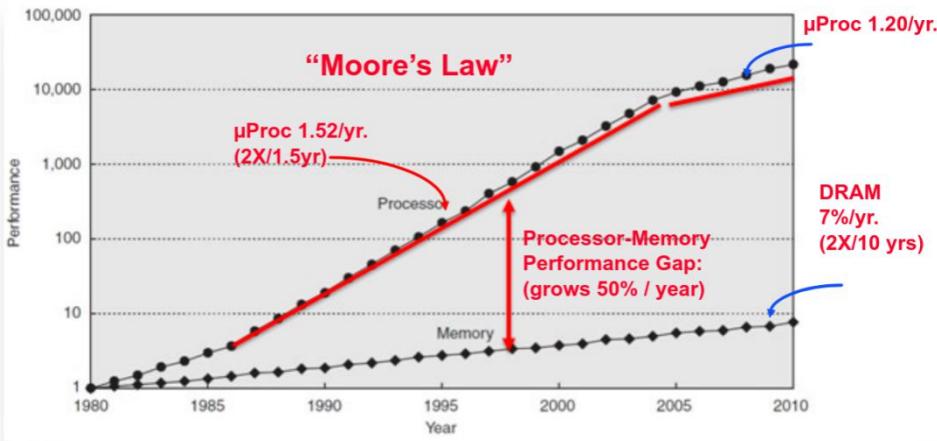


Modern
Architecture

The Memory



Early 90s: CPU becomes faster than memory



Processor	Alpha 21164	
Machine	AlphaServer 8200	
Clock Rate	300 MHz	
Memory Performance	Latency	Bandwidth
I Cache (8KB on chip)	6.7 ns (2 clocks)	4800 MB/sec
D Cache (8KB on chip)	6.7 ns (2 clocks)	4800 MB/sec
L2 Cache (96KB on chip)	20 ns (6 clocks)	4800 MB/sec
L3 Cache (4MB off chip)	26 ns (8 clocks)	960 MB/sec
Main Memory Subsystem	253 ns (76 clocks)	1200 MB/sec
Single DRAM component	≈60ns (18 clocks)	≈30–100 MB/sec

Taken from a 1997 paper

The CPU may spend more time waiting for data coming from RAM than executing ops. That is part of the so called “memory wall”. What is the solution ?



A note about today

You certainly know that DDRAM memory frequency increased in the last year up to 3-4GHz

However, that alleviate the problem only partially

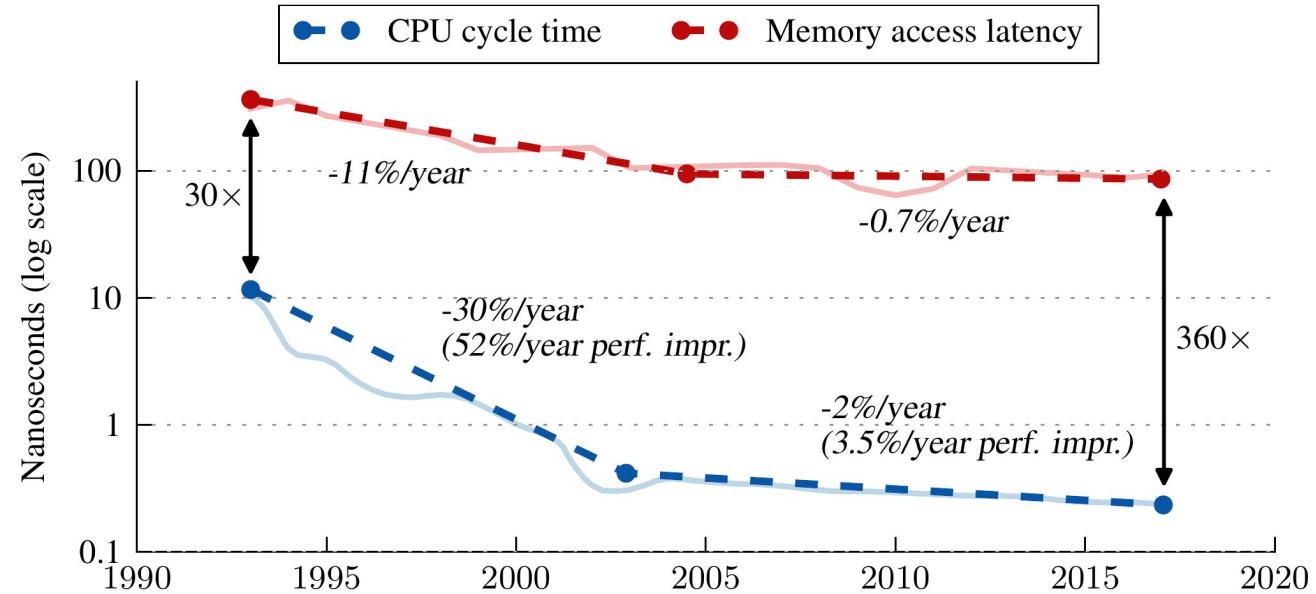


Figure taken from:
"Memory Bandwidth and Latency in HPC: System Requirements and Performance Impact"

Ph.D dissertation thesis, 2019, Dep.t of Computing
Architectures, UPC

Figure 2.4: Increasing discrepancy between main memory access latency and CPU cycle time, for last 25 years. Recently the downtrend in CPU cycle time decreased to 2%, while single processor performance improves at 3.5% per year [52]. The decrement in memory access latency is less than 1%.



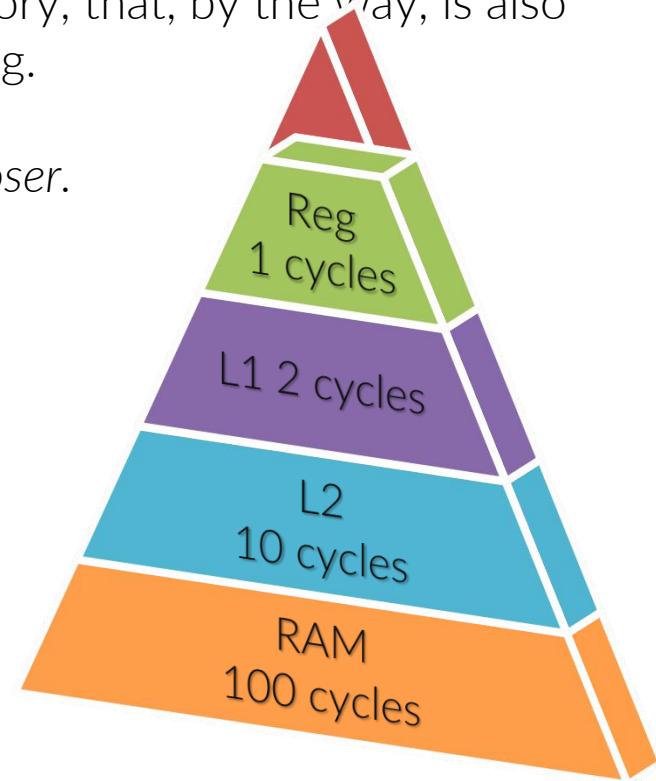
The cache memory

The solution is to equip your CPU with a *faster* memory, that, by the way, is also way more expensive and way more energy consuming.

Furthermore, to be faster it ought to be *extremely closer*. All in all, the new memory that will be called **cache**, will be much *smaller* than RAM.

The cache itself has a hierarchy:

- Level-I is inside each core.
- Level-II is also inside the core, or may be shared by more cores.
- Level-III is inside the CPU, shared by many cores.



Just a quick curiosity: the origin of the word “cache” is linked to winery.

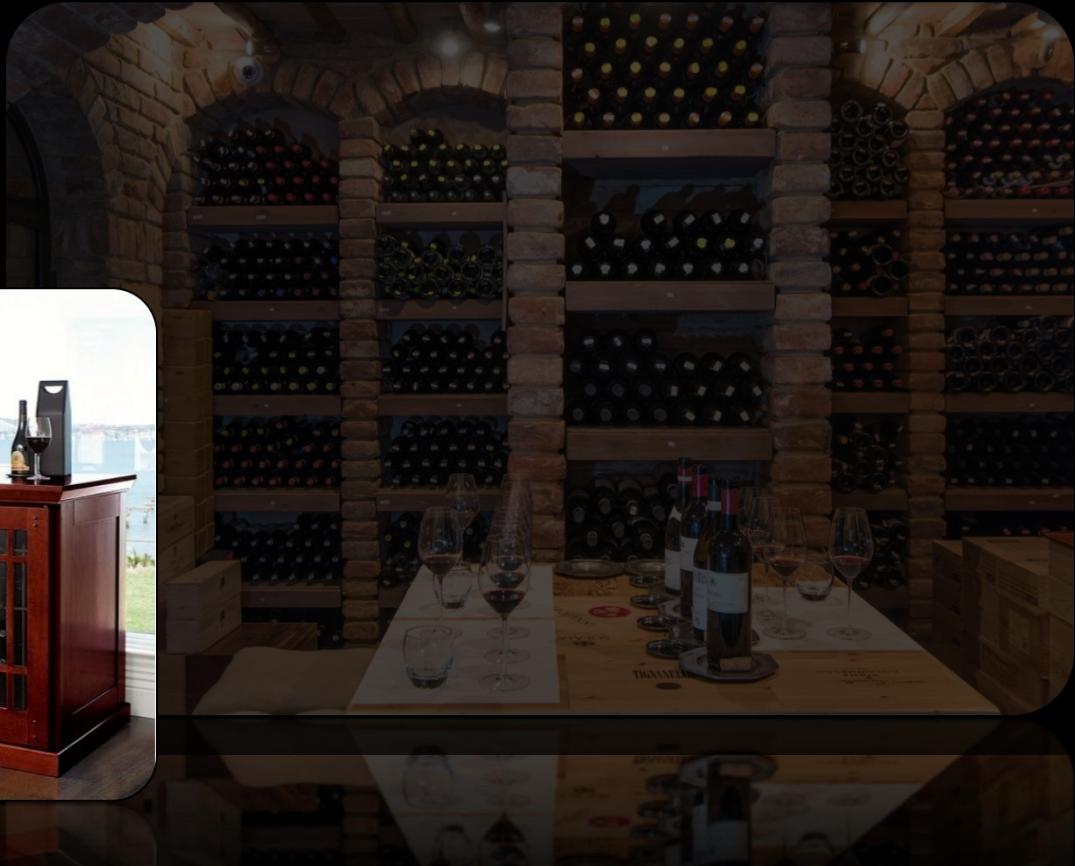
While you have the bulk of your precious wines in the basement cellar, it may be uncomfortable to get back and forth while you are dining with friends..



Just a quick curiosity: the origin of the word “cache” is linked to winery.

That's why you are backing up with your **cache**, which you have pre-emptively filled with the most suited^(*) wines !

() Then, if one of your guests asks for a different wine, you will have to get back to your cellar... Which is exactly the point we'll arrive at.*



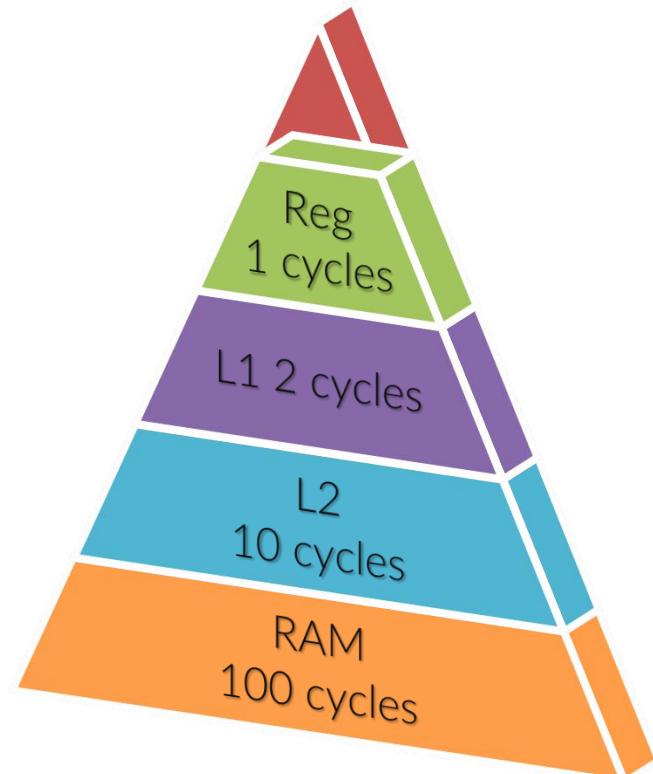


The cache memory

L1 cache + RAM

$$L_{1\text{cost}} + Miss_1 \times RAM_{\text{cost}}$$

- 100% L1 hit → 2 cycles
 - 99% L1 hit → 3 cycles
 - 97% L1 hit → 5 cycles
- } 50% to 150% slower





The cache memory

L1 cache + RAM

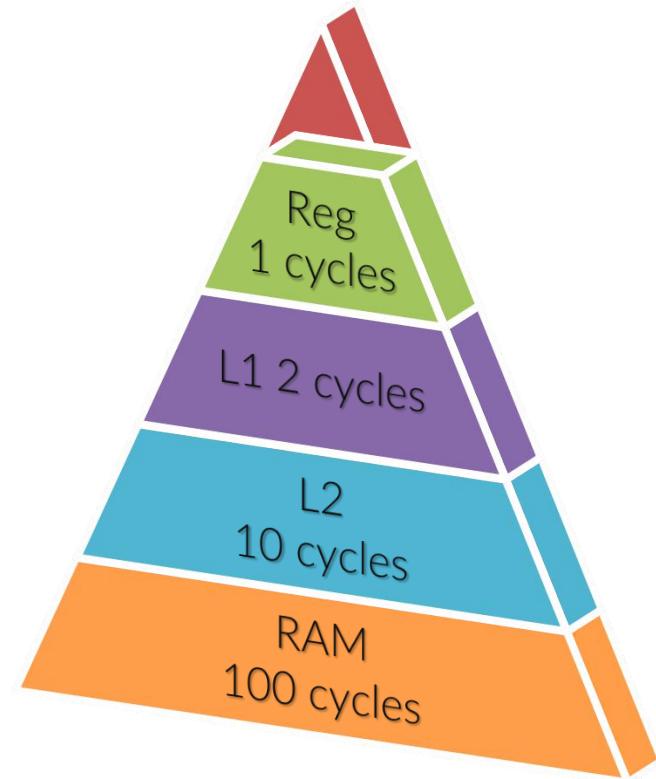
$$L_{1cost} + Miss_1 \times RAM_{cost}$$

- 100% L1 hit → 2 cycles
- 99% L1 hit → 3 cycles
- 97% L1 hit → 5 cycles

L1 cache + L2 cache + RAM

$$L_{1cost} + Miss_1 \times (L2_{cost} + Miss_2 \times RAM_{cost})$$

- 100% L1 hit → 2 cycles
- 99% L1 hit, 100% L2 hit → 2.1cycles
- 97% L1 hit, 100% L2 hit → 2.3 cycles
- 90% L1 hit, 97% L2 hit → 3.3 cycles





The principle of locality

We are quite naturally led to the “principle of locality”:

Data are defined “local” when they reside in a “small”portion of the address space that is accessed in some “short” period of time

→ local data are likely to be in the cache

- | | |
|--------------------------|---|
| Temporal locality | if an address is referenced, it is likely to be referenced again soon |
| Spatial locality | if an address is referenced, close addresses are likely to be referenced soon |



Cache mapping

Question:

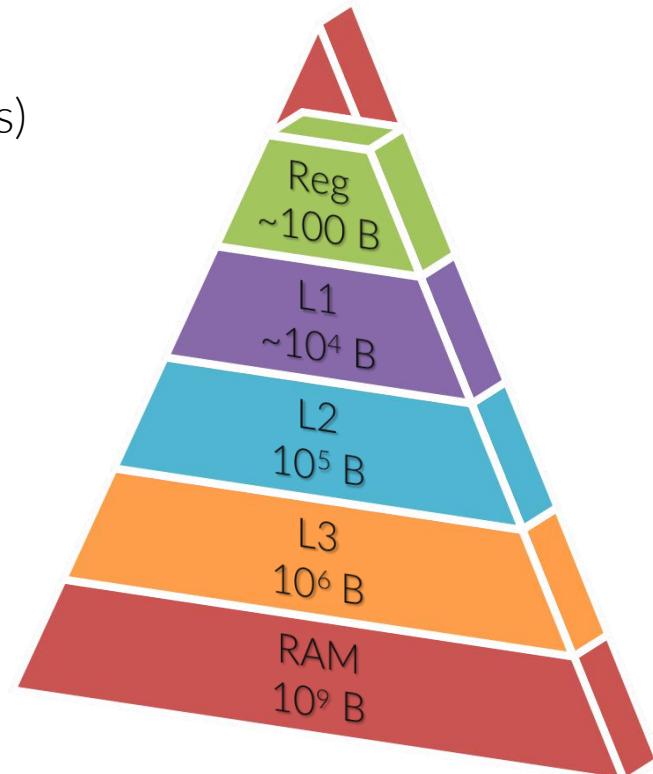
The RAM contains $\sim 10^9$ bytes, while L1 contains $\sim 10^4$ bytes (32KB for data and 32KB for instructions)

So, how do you map the RAM in to a given level of cache, for instance L1, in an effective way?

The main problems are:

- Where to map an address
- What if the location in L1 is already occupied?

...we'll see that in the next lecture





Cache recap in two slides

**3C for the
foes**

▶ **Compulsory misses**

Unavoidable misses when data are read for the first time

▶ **Capacity misses**

- Not enough space to hold all data
- Too much data accessed in between successive use

▶ **Conflict misses**

Cache trashing due to data mapping to same cache lines



Cache recap in two slides

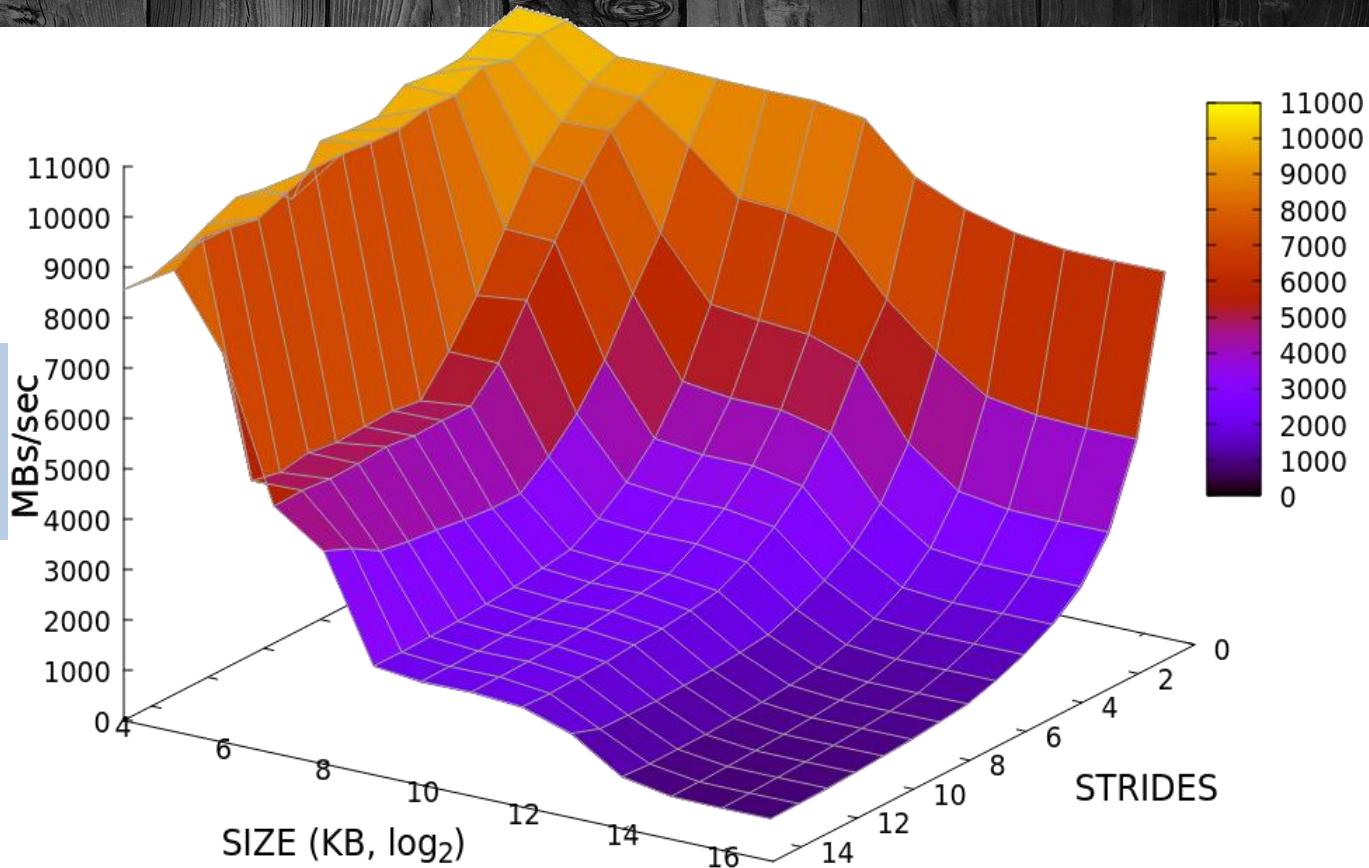
**3R for the
friends**

- ▶ **Rearrange (code & data)**
Design layout to improve temporal & spatial locality
- ▶ **Reduce (size)**
 - Smaller data size – smaller chunks accessed
 - Fewer instructions
- ▶ **Reuse (cache lines)**
Increase spatial & temporal locality – keep resident data for more operations



Preview: The memory access pattern

The result is..
the memory mountain



Just a preview;
more details in the next lecture

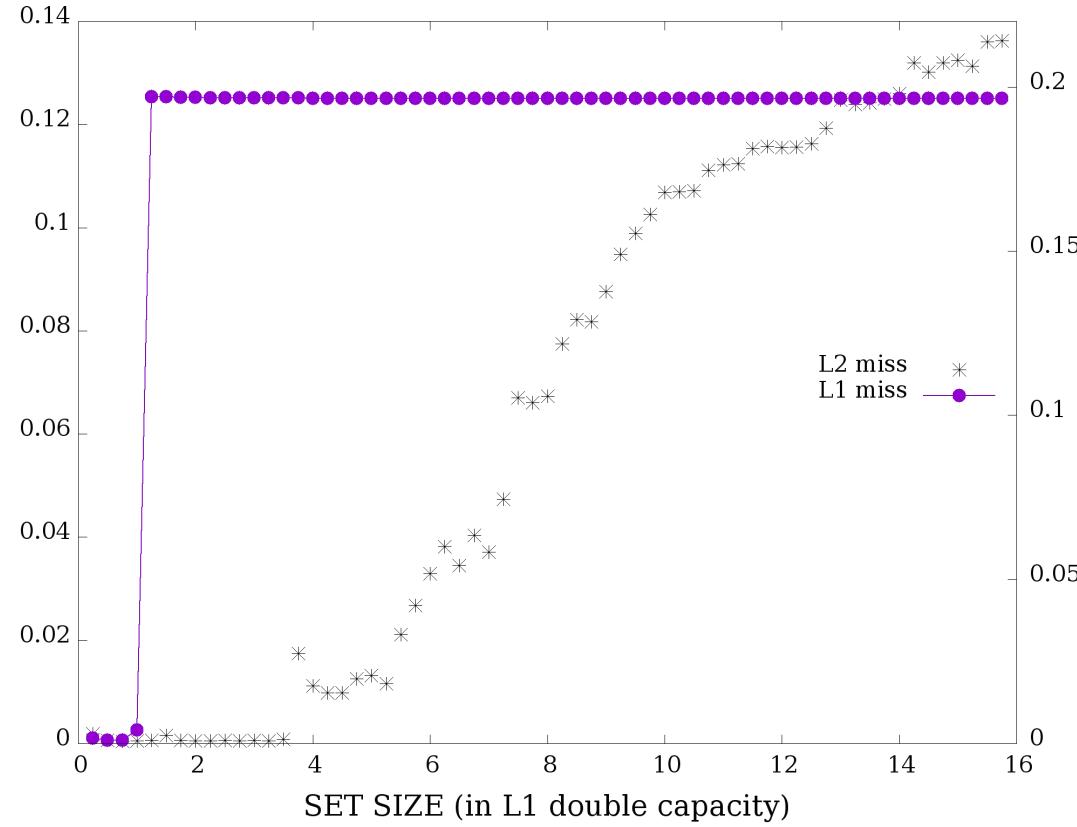


Preview: The cache-miss signature

Let's find out our
cache size

```
for (j=0; j < size; j++)  
    array[j] =  
        2.3*array[j]+1.2;
```

Just a preview;
more details in the next lecture



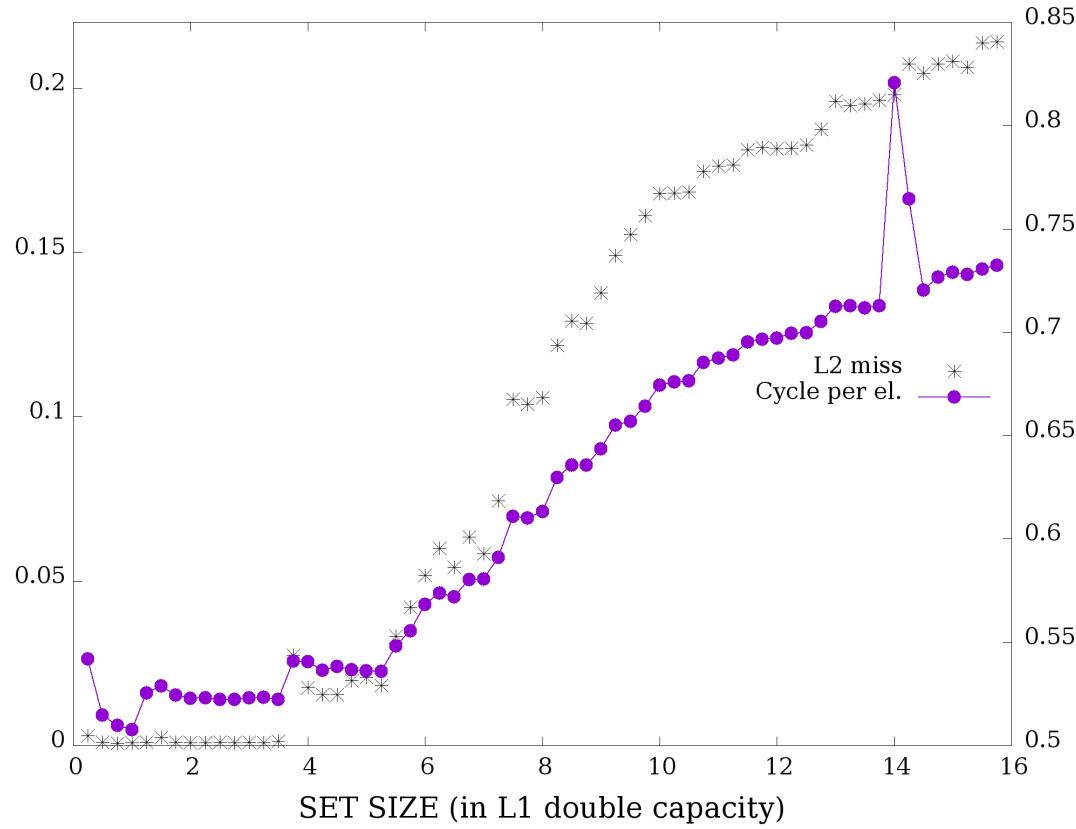


Preview: The cache-miss signature

And the effect on
cycles-per-operation
metrics

```
for (j=0; j<size; j++)  
    array[j] =  
        2.3*array[j]+1.2;
```

Just a preview;
more details in the next lecture

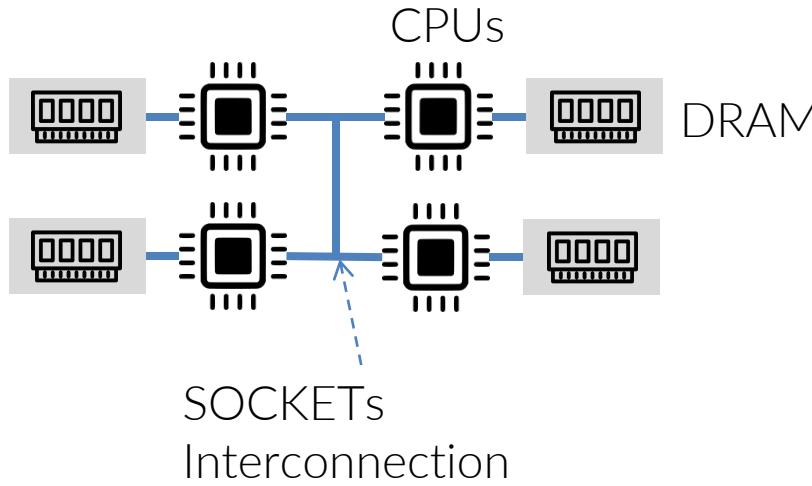




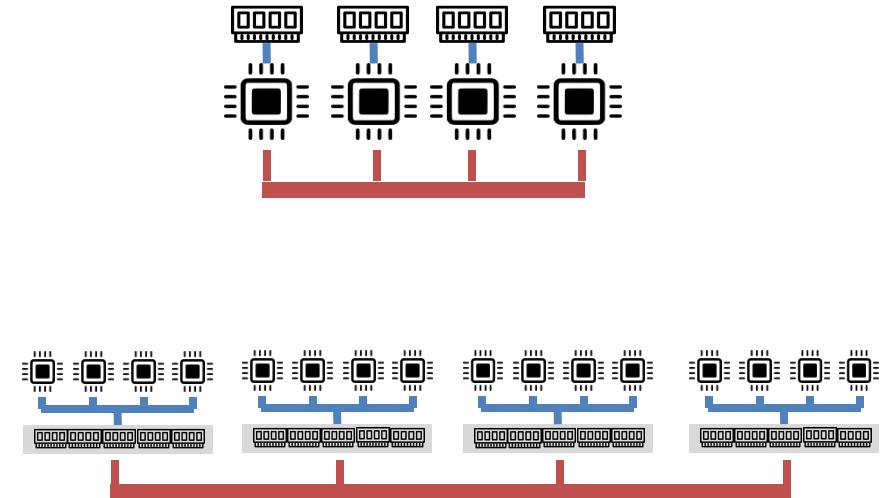
A coherency problem

You already know the difference between

SMP



Distributed NUMA

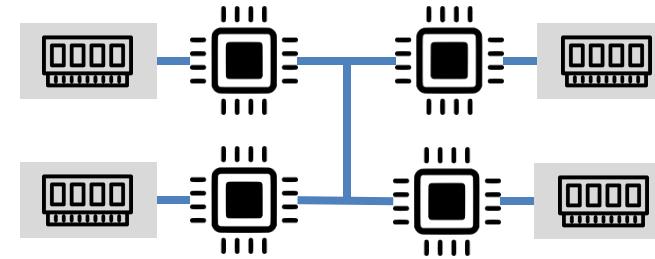




A coherency problem

Consider an SMP node, with tens of sockets interconnected by an interconnection, which behaves similarly to a bus

(remind: a **bus** is a “collective” interconnect in which the messages are broadcasted and everyone is listening for a message dedicated to itself)

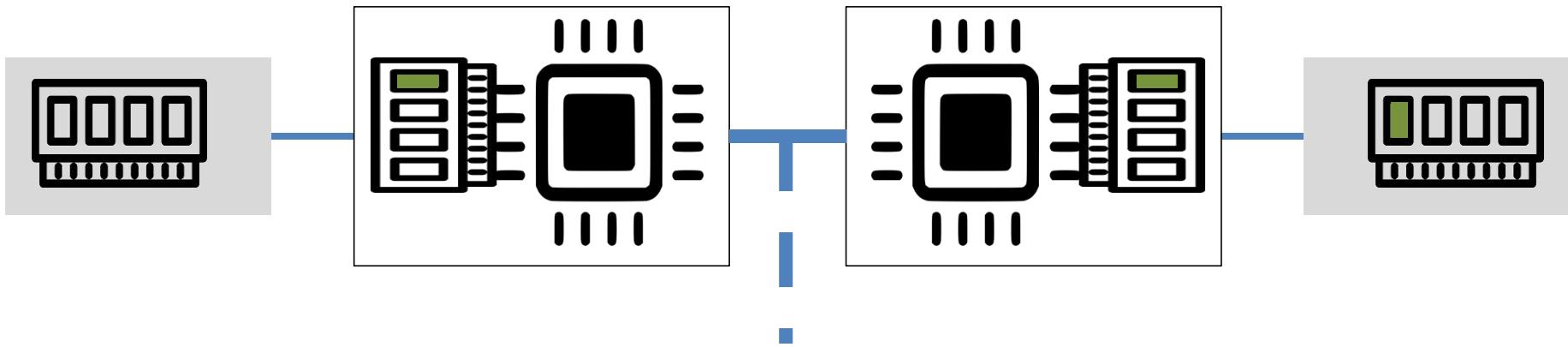


The memory is *shared*, and everybody sees the whole amount of RAM



A coherency problem

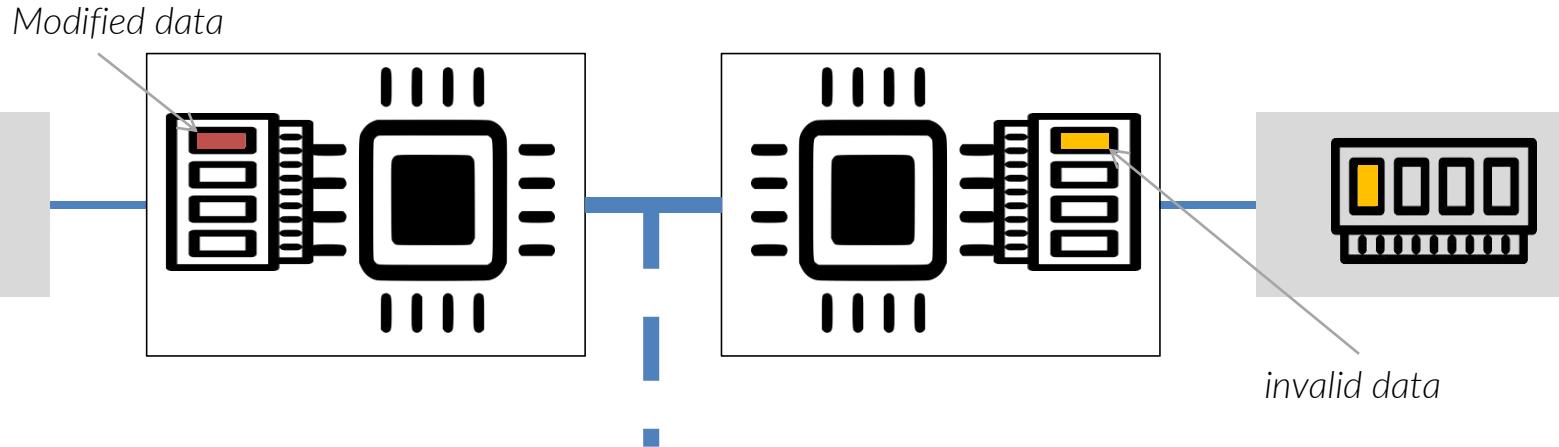
Let's say that the CPUs have caches and some data are loaded in more than one cache





A coherency problem

Let's say that the CPUs have caches and some data are loaded in more than one cache



What happens to all the caches and “actual” data in memory when one CPU modifies the data?

That is called *cache coherency* and the overwhelming difficulty and cost to manage it on too large SMP nodes is the main limit to their size.



Early 90s: CPU becomes faster than memory

So, after having introduced the hierarchy of cache memories, you have to deal with a strong memory hierarchy and the fact that your CPU is much faster than the central memory.

Even if you are very good in designing the data model and the workflow of your code, that complexity may result in a real performance disaster: for instance because your CPU is stuck doing nothing while waiting for some data or for some operation to end.

This leads us to some more improvements.



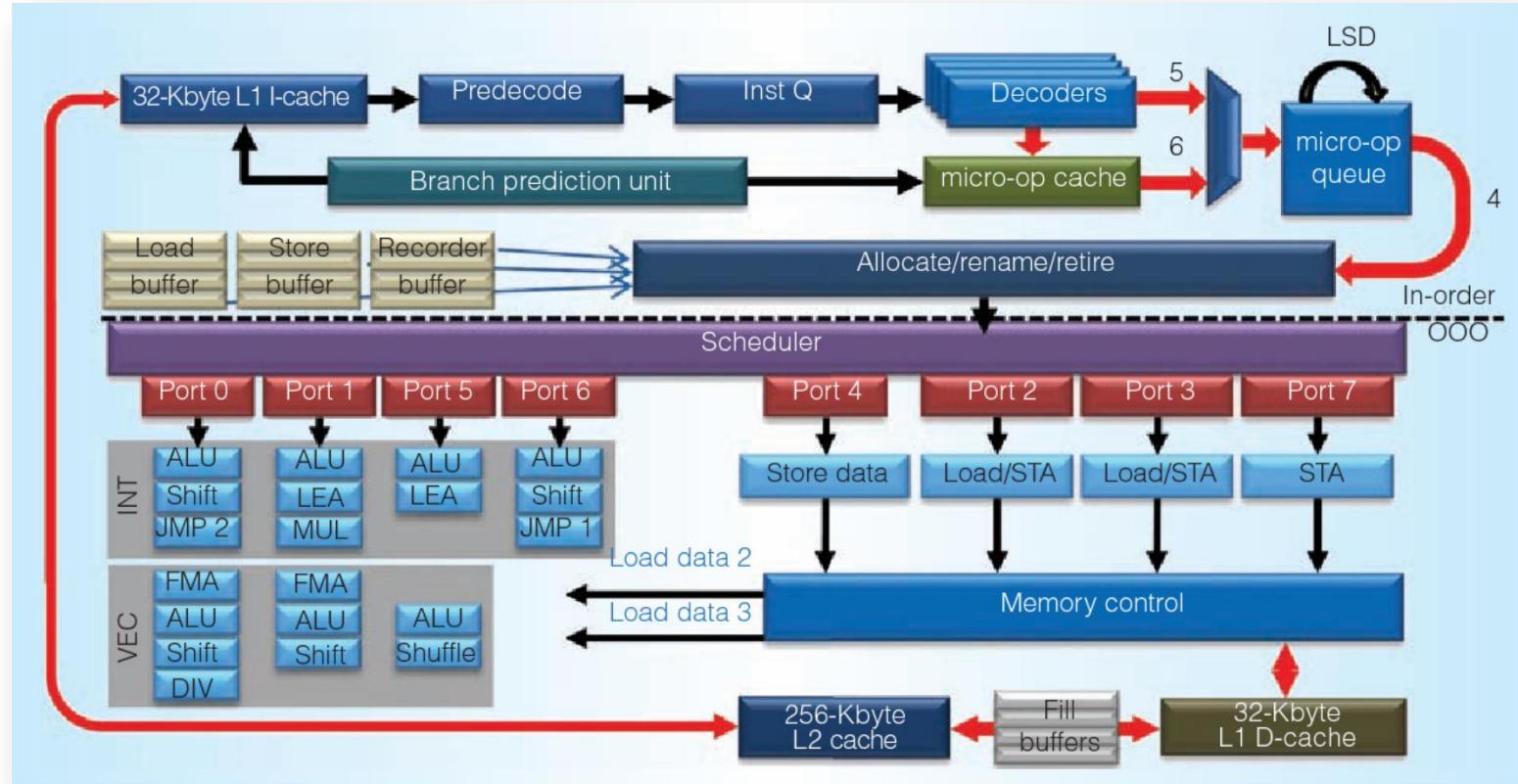
Modern
Architecture

OoO, ILP, Pipelines, Vectors

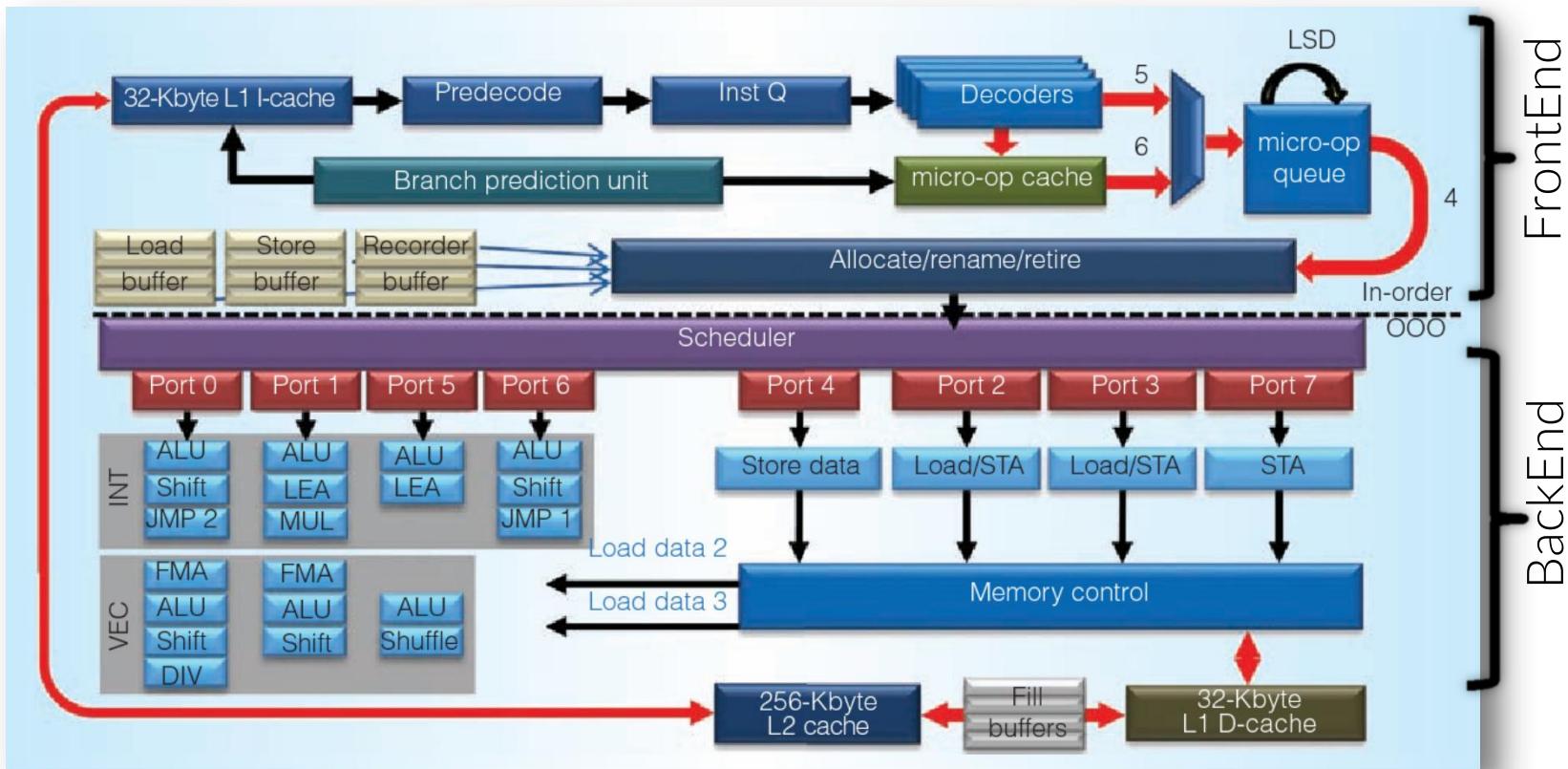


Mid 90s: superscalar and out-of-order CPUs

6th generation
SkyLake
micro-arch.

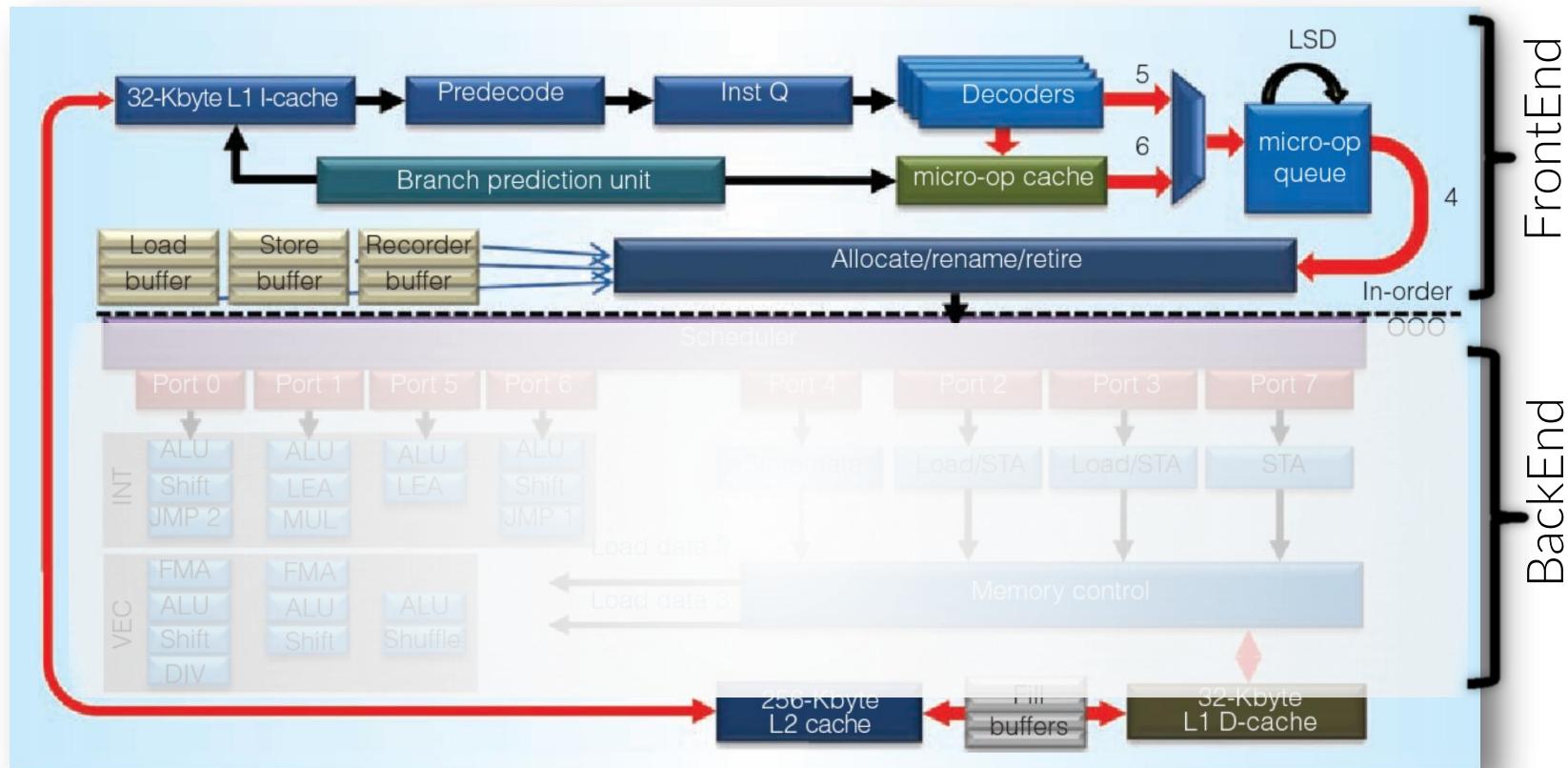


More than 1 port is available to execute CPU instructions, although different units have different specializations (ALU, LEA, SHIFT, FMA, ...) : that is **superscalar capacity**, i.e. the capacity of executing more than 1 instructions per cycle.



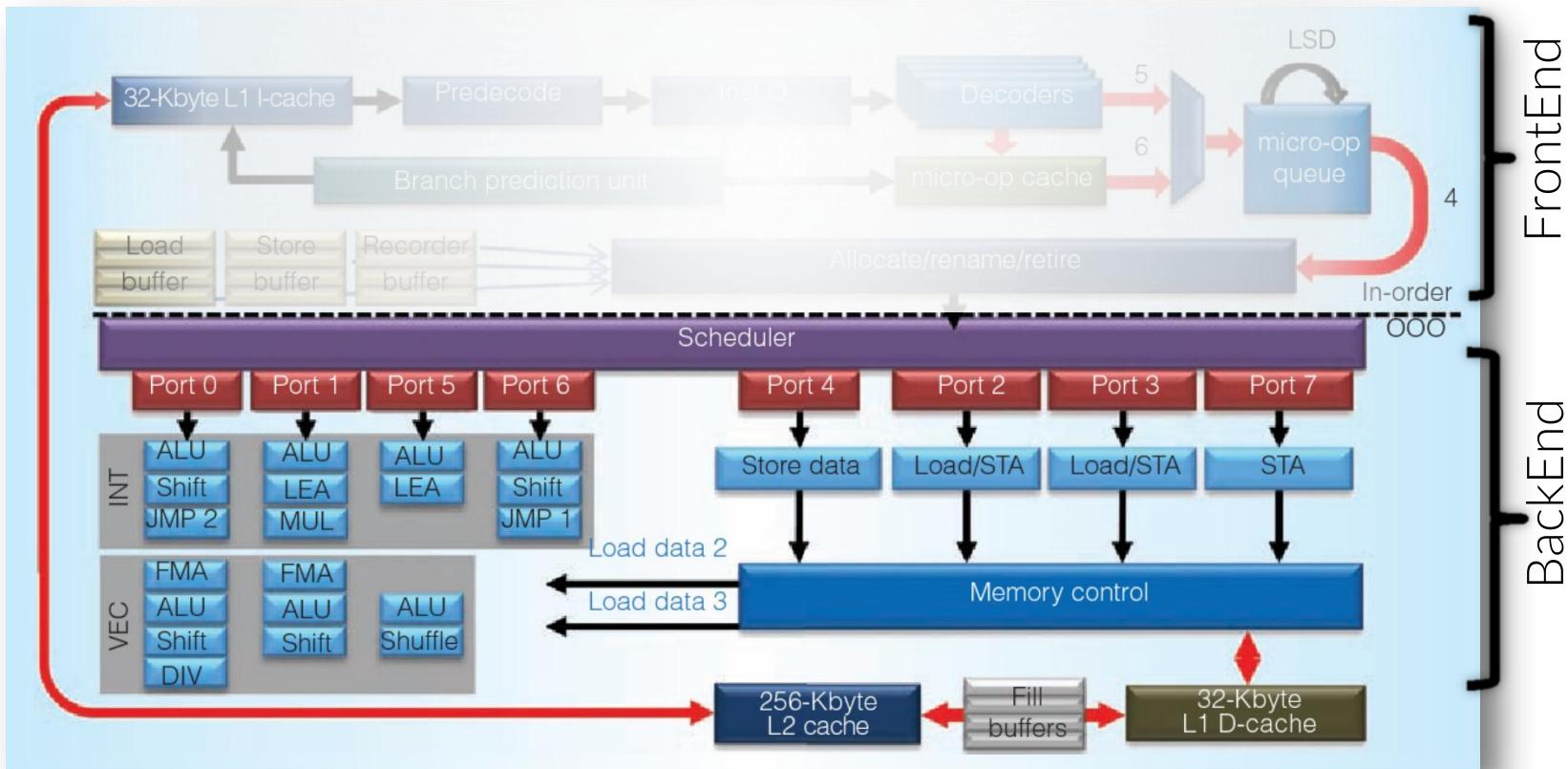
6th generation
SkyLake
micro-arch.

The Front-End basically fetches instructions and the data they operate on from instruction and data caches, decodes instructions, predicts branches and dispatches the instructions to different ports



6th generation
SkyLake
micro-arch.

The Back-End is responsible for the actual instructions execution and for the back-writing of results in memory locations. It is responsible also for orchestrating **out-of-order** ops execution depending on their instructions/data dependencies.



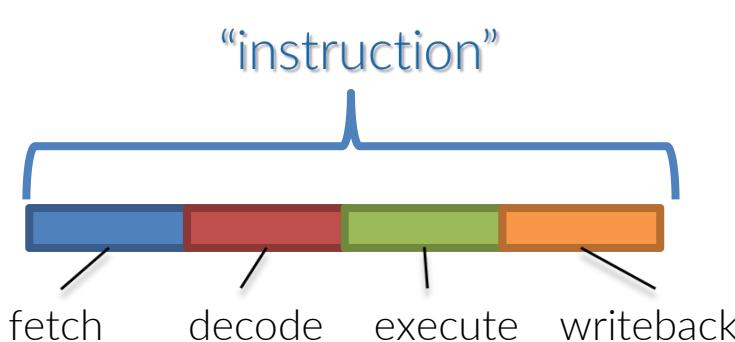
6th generation
SkyLake
micro-arch.



Pipelines

It would be obvious to think that an “instruction” is a kind of *atomic* operation that the CPU perform as a whole. Indeed that was true until the mid of the 80s.

If you think carefully about it, it is easy to understand that actually an “instruction” involves at least the following **independent** steps:



1. **Fetching**

it must be recalled from memory/lcache

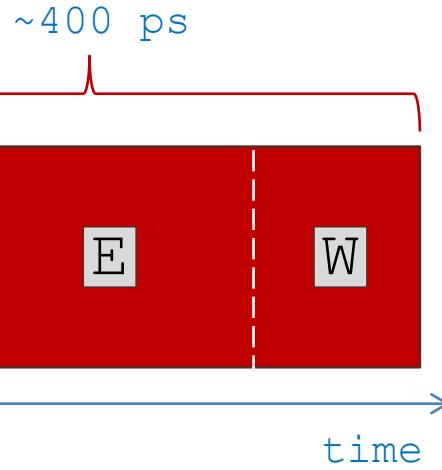
2. **Decoding:**

it must be “understood and interpreted”

3. **Execution**

4. **Writeback :**

the result must be accounted in memory ()



If all the four stages take $\sim 400\text{ps}$, we then would obtain a **throughput** of 2.5GIPS (giga-instructions per second).

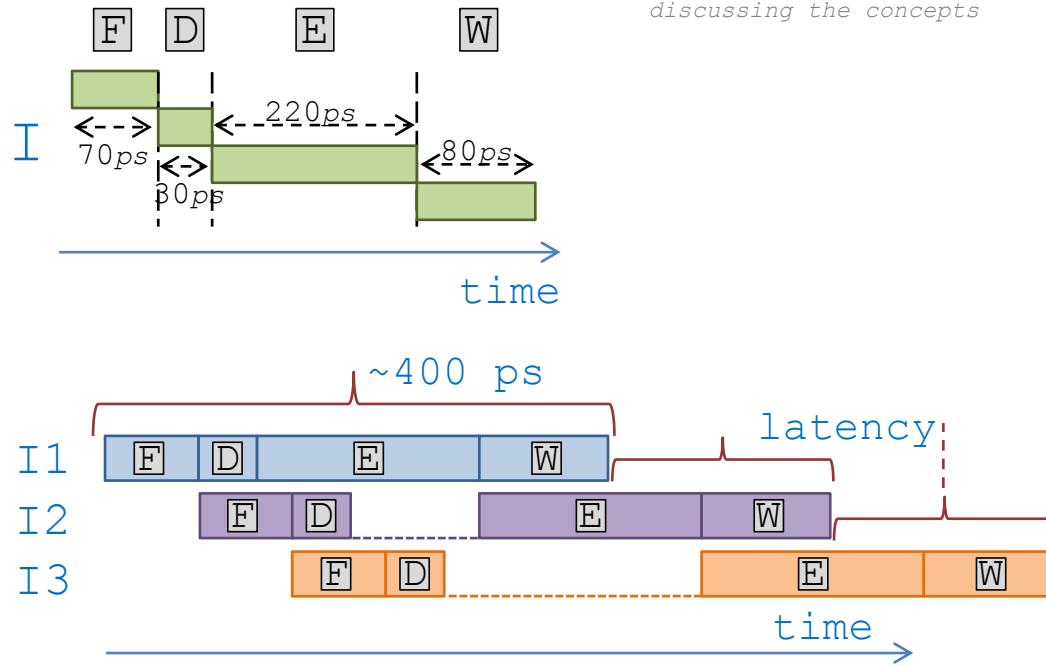
400ps is also the total time required to get a result from an instruction, and so it is the **latency** of the instruction.

However, if we were able to “detach” the four stages, we could organize things differently, like in a car-building chain, or even at the mensa of the university.



Pipelines

Note: all the timing estimates are hypothetical for the purpose of discussing the concepts



If many independent logical units exist to perform each step, they could operate subsequently on **different instructions**:

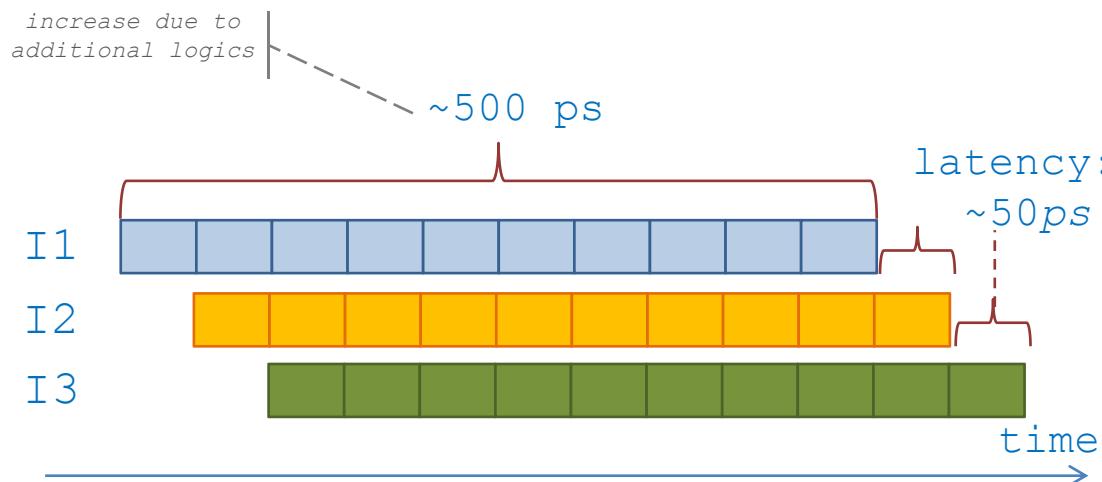
If the stage delays are not uniform, the throughput is limited by the latency $F + (D+E) - (F+D) = E \sim 220\text{ps}$, which means we have a throughput of **~4.5GIPS** just because of logic units separation.



Pipelines

Therefore, introducing the instructions pipelining, we can increase the **throughput** of our system by a large factor.

However, the efficiency of the pipelines is limited by its longest stage: the better option would be to have all equal stages, for instance further subdividing each stage – especially the most demanding ones (*).



Now the throughput of our system has increased to 1 instruction retired every 50ps, i.e. **20GIPS**

(*) this is called *superpipelining*: modern CPUs may have 10-20 stages per pipeline.



Pipelines are about throughput

Pipelining is then about increasing the throughput of a system, and as we have seen it could be really effective.

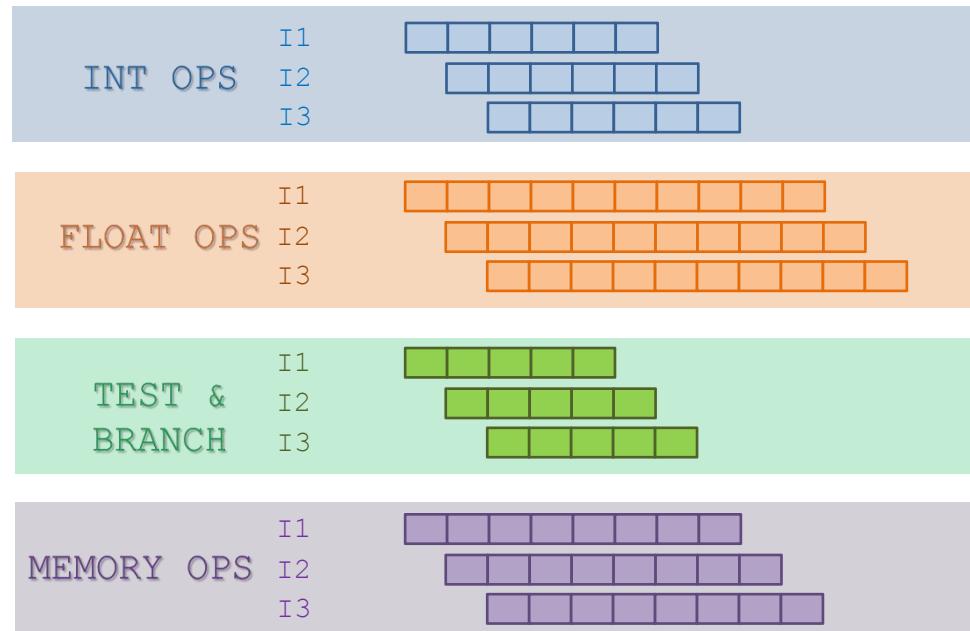
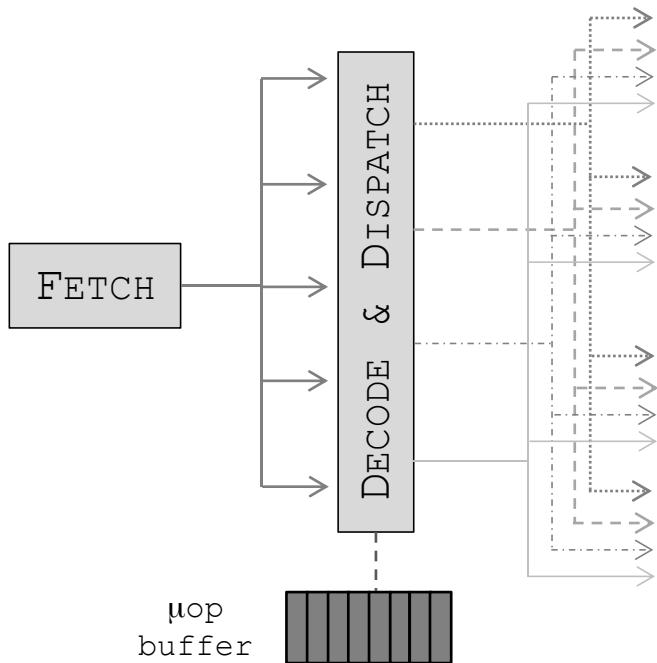
However, there is more that can be done working on the **execution stage** that, of course, encompasses a large number of different **functional units**, performing a **different and independent tasks**.

With an enhancement of the decode/dispatch stage, we can address multiple pipelines that can be active at the same time:



Pipelines

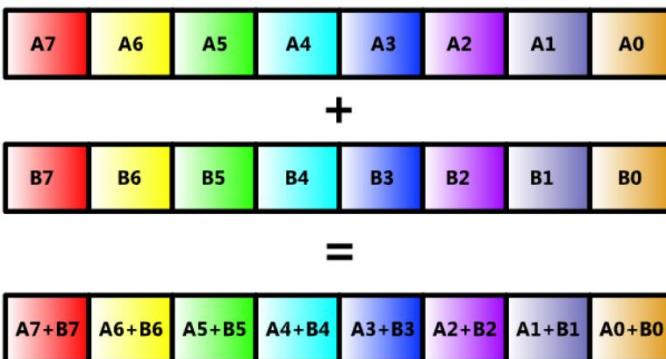
Multiple pipelines



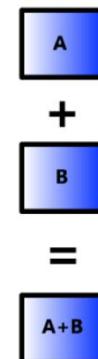


https://software.intel.com/sites/default/files/m/d/4/1/d/8/Intro_to_Intel_AVX.pdf

SIMD Mode



Scalar Mode



Vector registers are large special registers in the CPU that can be considered subdivided in smaller independent chunks over which the same operation can be performed:

SIMD: Single Instruction
Multiple Data



Vector registers size

SSE Data Types (16 XMM Registers)

<code>_m128</code>	Float	Float	Float	Float	4x 32-bit float
<code>_m128d</code>	Double		Double		2x 64-bit double
<code>_m128i</code>	B	B	B	B	16x 8-bit byte
<code>_m128i</code>	short	short	short	short	8x 16-bit short
<code>_m128i</code>	int		int	int	4x 32bit integer
<code>_m128i</code>	long long		long long		2x 64bit long
<code>_m128i</code>	doublequadword				1x 128-bit quad

AVX Data Types (16 YMM Registers)

<code>_mm256</code>	Float	Float	Float	Float	Float	Float	Float	Float	8x 32-bit float
<code>_mm256d</code>	Double		Double		Double		Double		4x 64-bit double
<code>_mm256i</code>	256-bit Integer registers. It behaves similarly to <code>_m128i</code> . Out of scope in AVX, useful on AVX2								



Modern
Architecture

Branches



Many Cores

That is the focus of the course on OpenMP
in the next days



Many Nodes

That is the focus of the course on MPI
that we will organise in the future

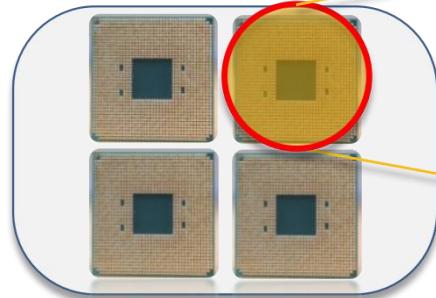


Heterogeneous devices

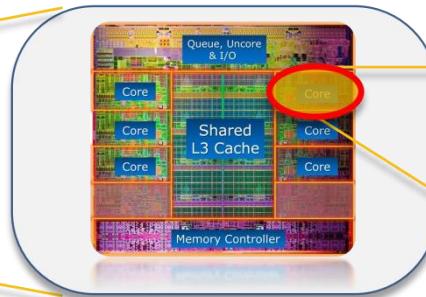
That is the focus of the course on GPUs
that we will organise in the future



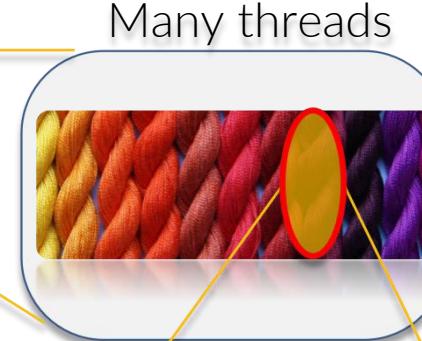
A final sketch



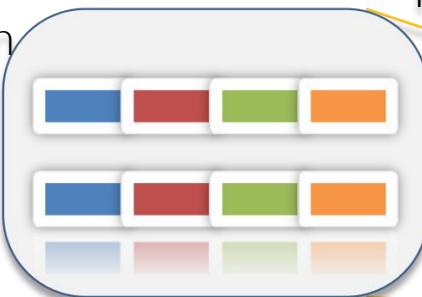
sockets



Many cores
per socket



Many threads



Vectorisation



Pipelining



Superscalarity



A final sketch

Data-Level
Parallelism

Instruction-Level
Parallelism

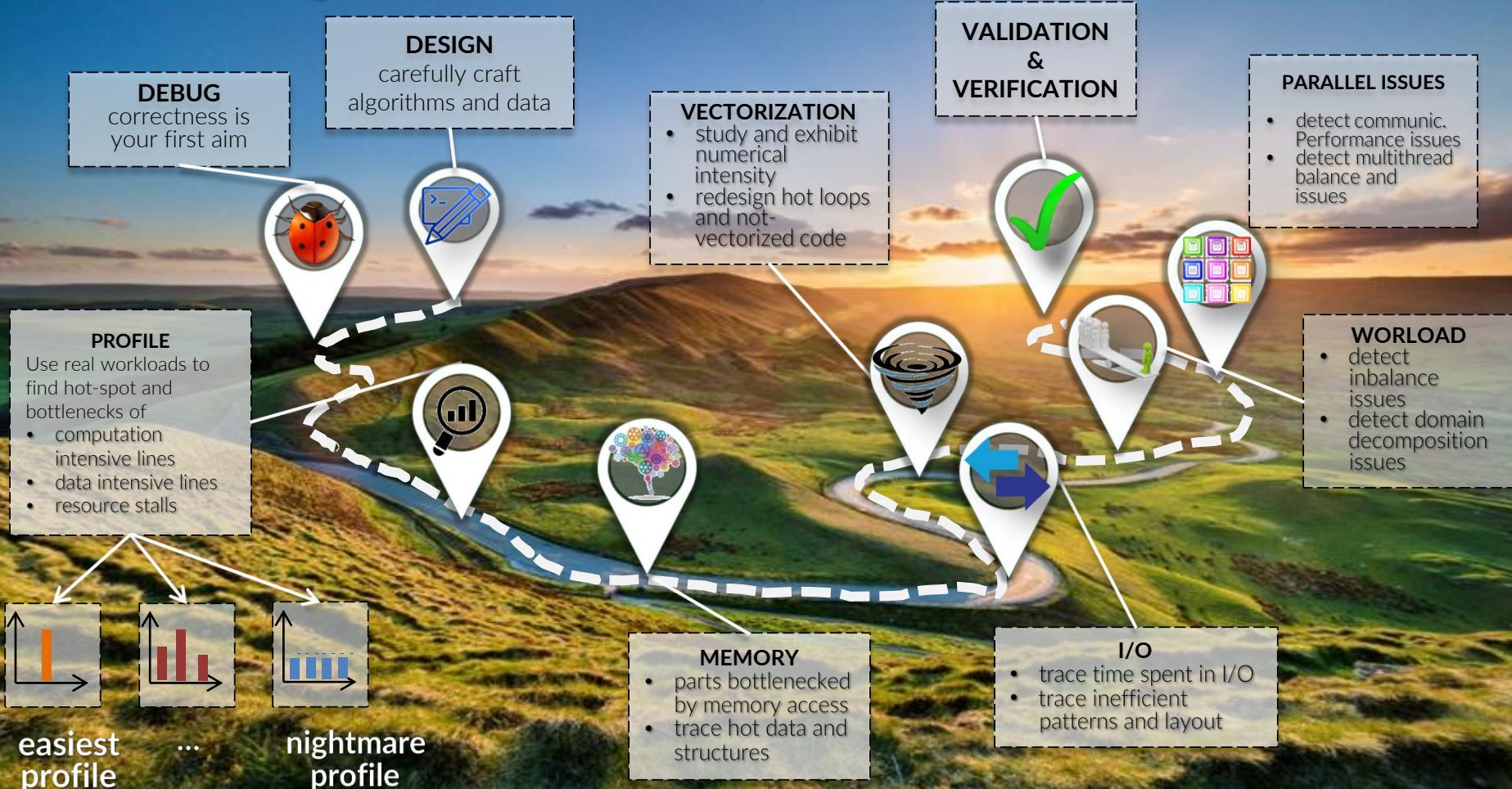
Thread-Level
Parallelism



The parallelism levels
in a computational
node.
*We'll get through each
of them separately.*

Thread-Level
parallelism will be
covered in the
OpenMP lectures

The winding road towards optimization



that's all, have fun

"So long
and thanks
for all the fish"