Introduction to Parallel Programming

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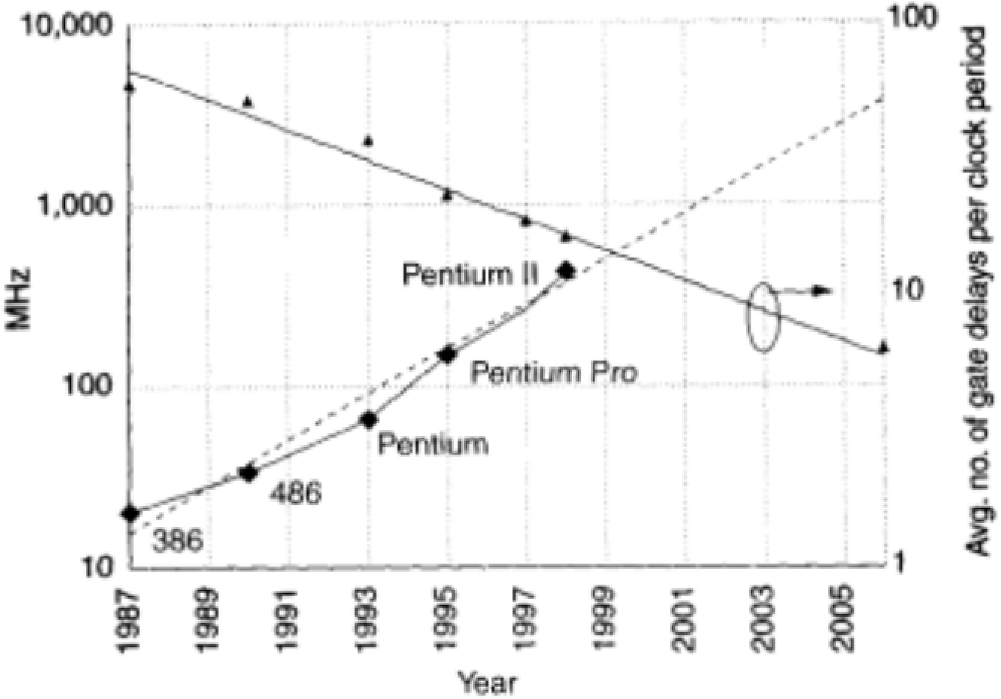
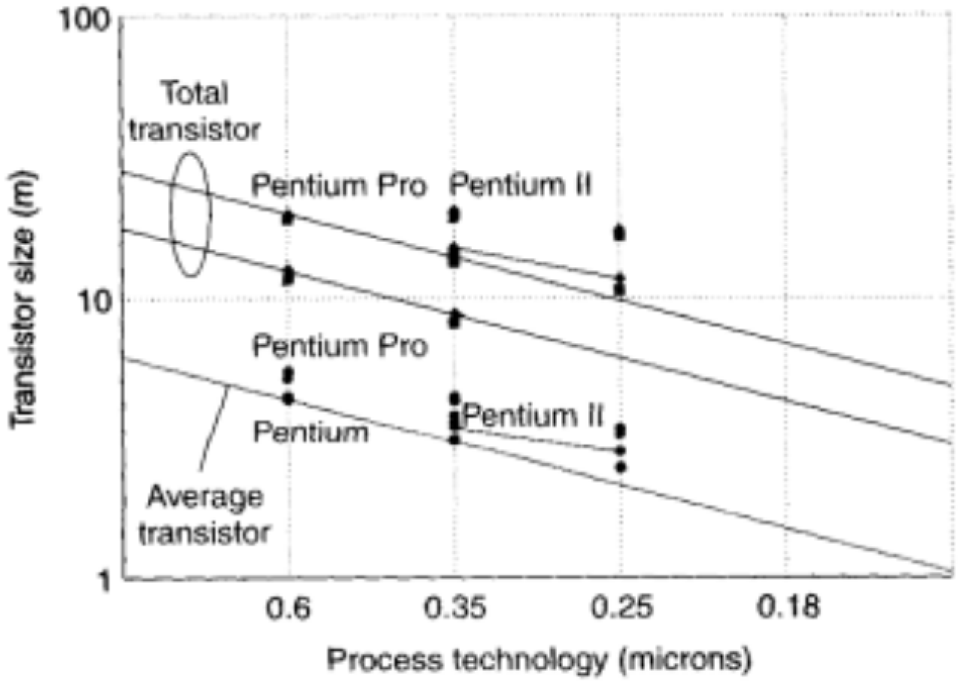
Real-time feedback

- click here
- Typos, confused explanations, bad examples
- This is very important to ensure the best teaching standards!

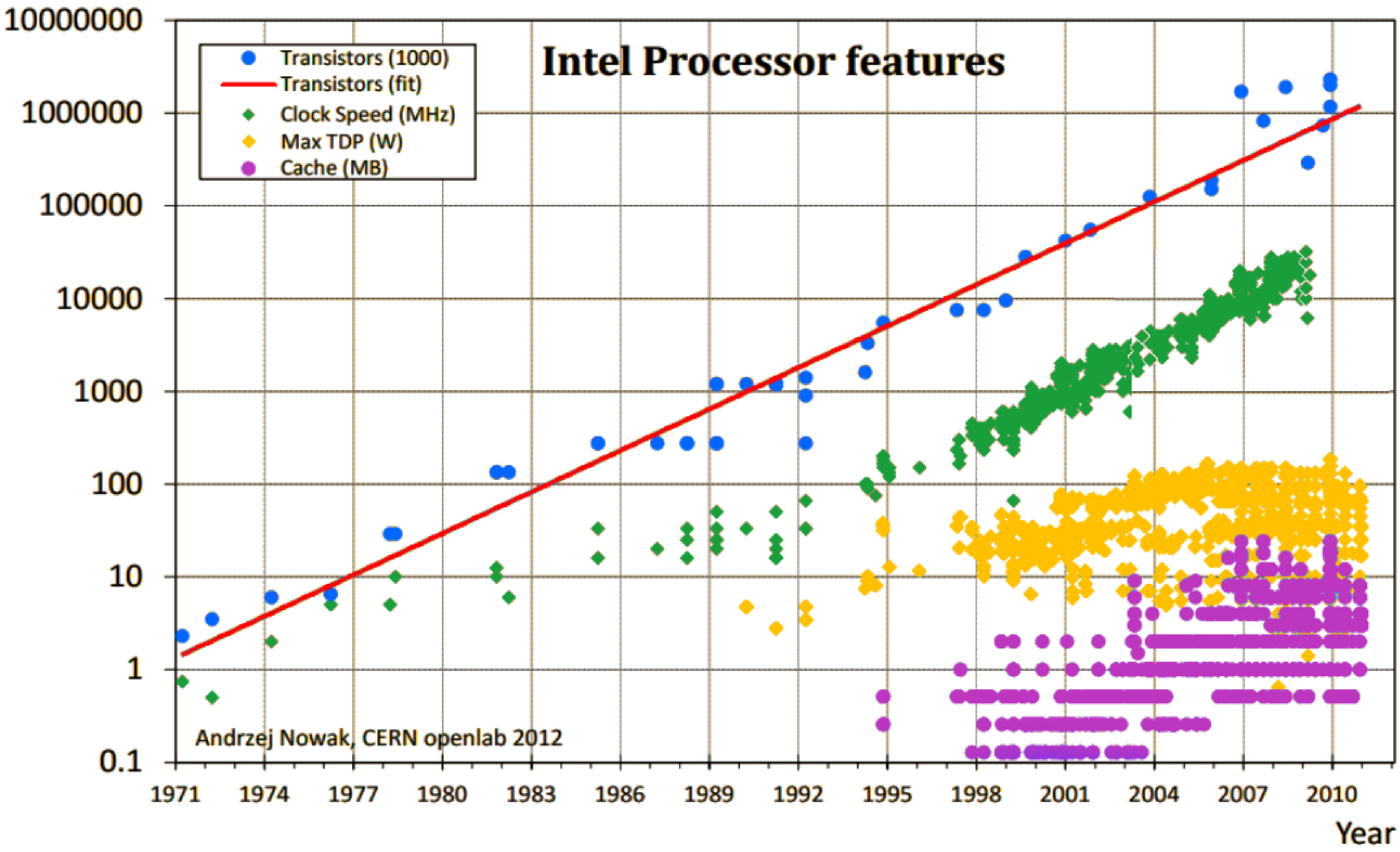
Previously, in Moore's Paradise



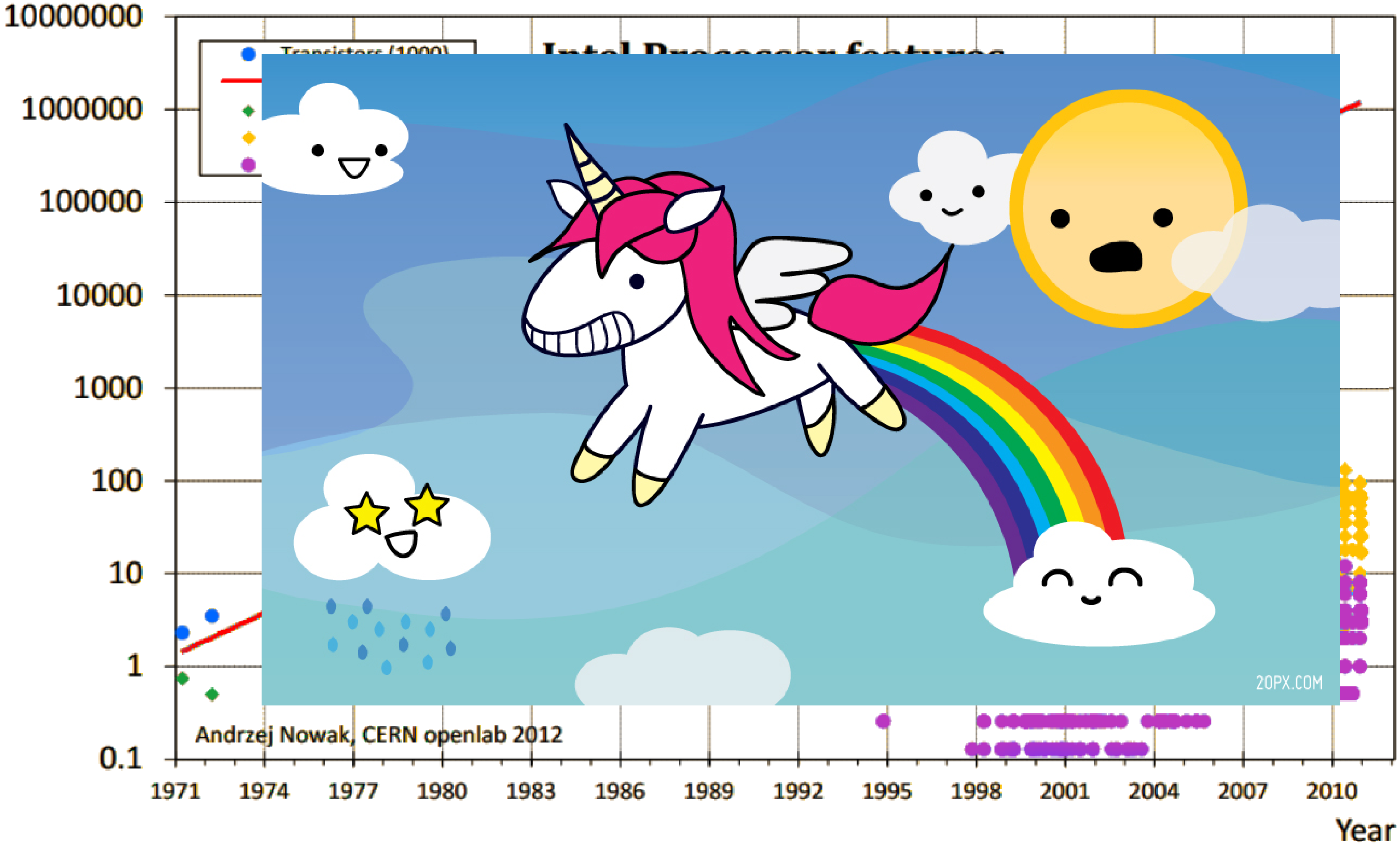


- The main contribution to the gain in microprocessor performance at this stage came by increasing the clock frequency.
- Applications' performance doubled every 18 months without having to redesign the software or changing the source code

Moore's Law (ctd.)

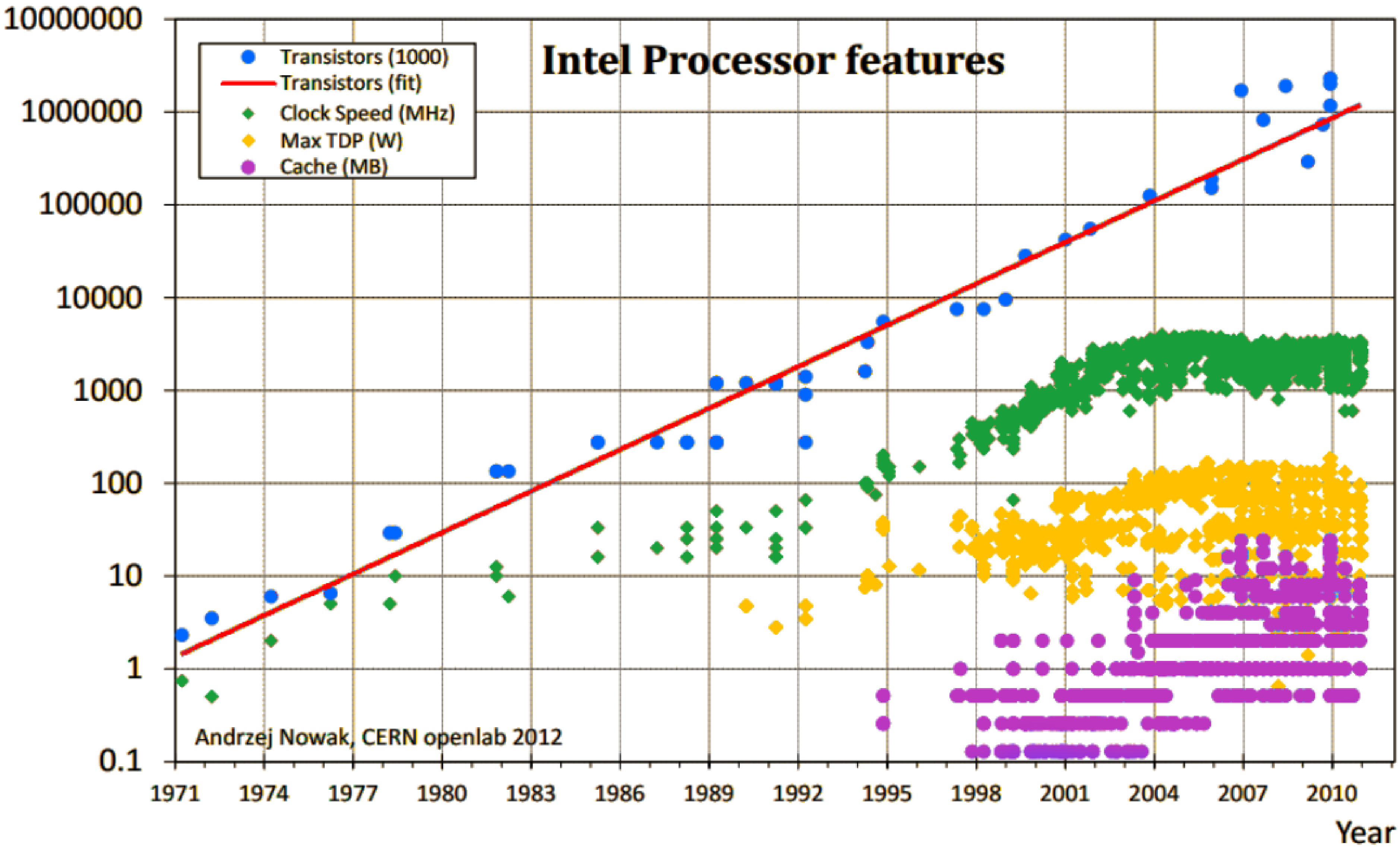


Moore's Law (ctd.)



Andrzej Nowak, CERN openlab 2012

Moore's Law (ctd.)



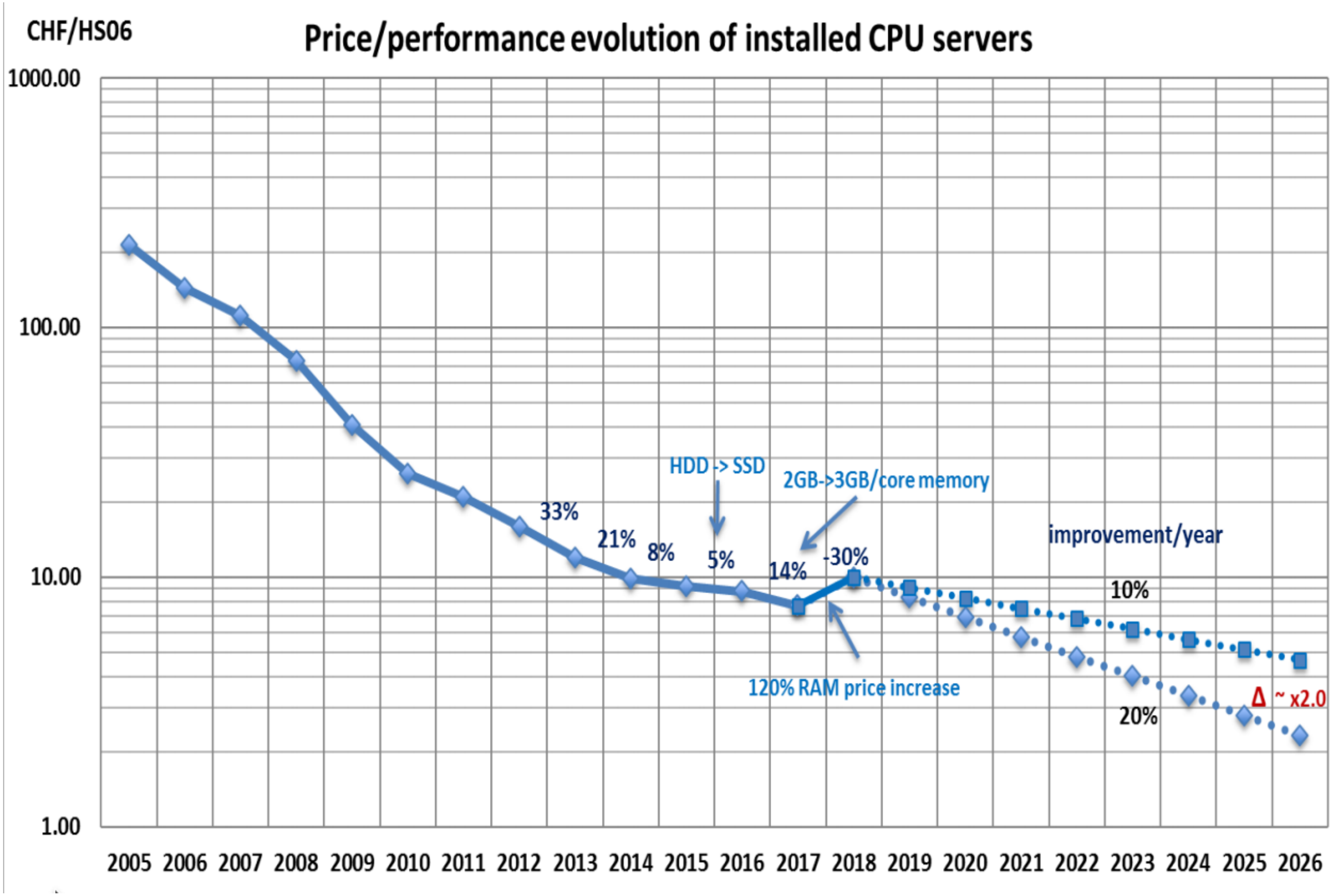
Back on Earth

- The power dissipated by a processor scales as

$$P = QCV^2 f + VI_{\text{leakage}}$$

- Q number of transistors
- C capacity
- V voltage across the gate
- f the clock frequency
- I current
- In the early 2000s, the layer of silicon dioxide insulating the transistor's gate from the channels through which current flows was just five atoms thick and could not be shrunk anymore

“The party isn't exactly over, but the police have arrived, and the music has been turned way down” (P. Kogge, IBM)

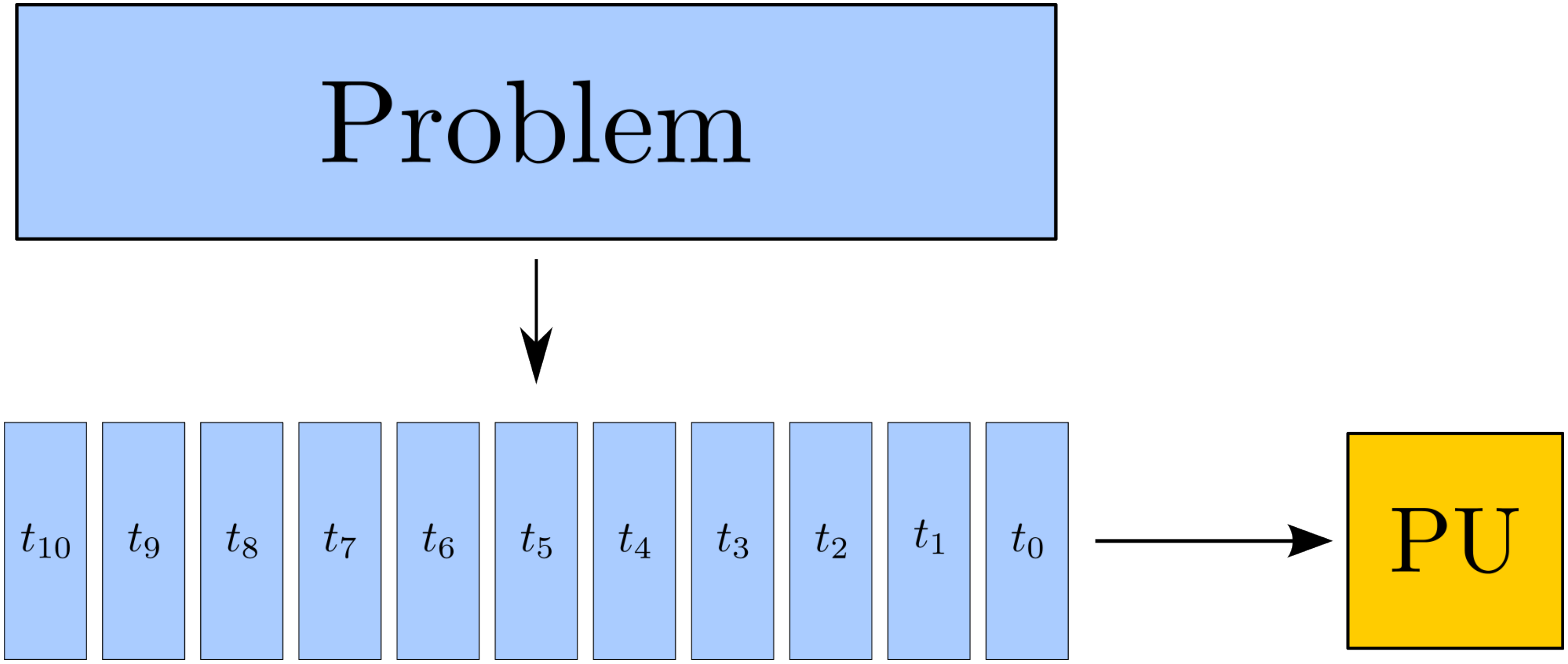

CHF/HS06
Price/performance evolution of installed CPU servers
1000.00
100.00
10.00
1.00
2005
2006
2007
2008
2009
2010
2011
2012
2013
2014
2015
2016
2017
2018
2019
2020
2021
2022
2023
2024
2025
2026
HDD -> SSD
2GB->3GB/core memory
33%
21%
8%
5%
14%
-30%
improvement/year
10%
120% RAM price increase
Δ ~ x2.0
20%

fetch, decode, execute

- The basic operation that every Processing Unit (PU) has to process is called instruction and the address in memory containing the instruction is saved
- A *Program Counter* holds the address of the next instruction
- *fetch*: the content of the memory stored at the address pointed by the Program Counter is loaded in a Instruction Register and the Program Counter is increased to point to the next instruction's address
- *decode*: the content of the Instruction Register is interpreted to determine the actions that need to be performed
- *execute*: an Arithmetic Logic Unit performs the decoded actions.

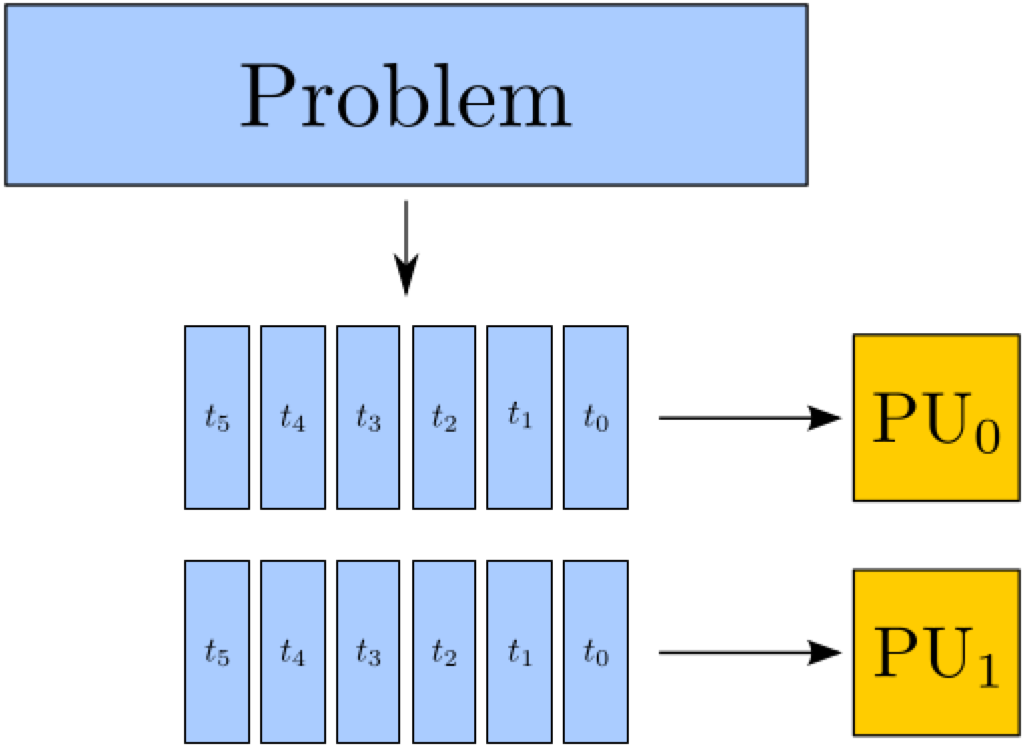
Serial computation

- Software traditionally written for serial computation:
- the sequence of instructions that forms the problem is executed by one Processing Unit (PU)
- every instruction has to wait for the previous one to be completed before its execution can start
- at any moment in time, only one instruction may execute



Parallel computation

- In parallel computation, if two instructions have no data dependency, they can be executed in parallel, at the same time, by two PUs



Pizza Wall

- How many cooks does a pizzeria need to achieve the best production rate possible?
- If all the ingredients are in the same fridge and there is only one oven? Maybe 1, 2, 64, infinity?

Mitigating the Pizza Wall

- Reuse of ingredients and tools which are used often: put them on a small table close to you
- Increase the frequency of travels to the fridge
- Increase the amount of ingredients you transfer from the fridge
- If ingredients are located all in the same box in the fridge, you can carry more of them with a single transfer

Memory Wall

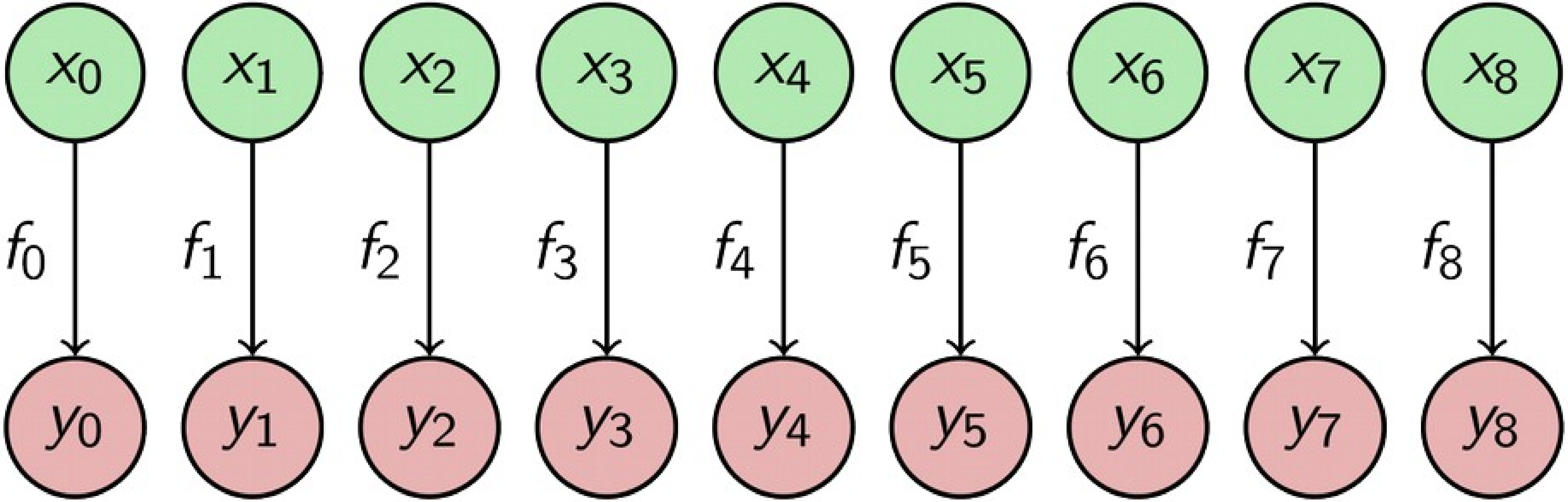
- How many PUs does a program need to achieve the best performance possible?

Mitigating the Memory Wall

- Reuse data and instructions: data and instructions which are used often are stored in a on-chip memory called cache.
- Increase the memory transfer speed: this can be done by increasing frequency, which is limited by the power wall.
- Increase the amount of data to transfer: memory transfers have overheads, which can become negligible if more memory is transferred in one instruction.
- Improve the access pattern to memory: if more processing units are reading adjacent memory locations, they can all be fed by a single memory transfer.

Embarrassingly parallel problems

$$y_i = f_i(x_i)$$



Embarrassingly parallel problems (ctd.)

Examples:

- Linear Algebra
- Image Processing
- Monte Carlo Simulation
- Bruteforce
- Weather forecast
- Random number generation
- Encryption
- Software compilation

Terminology

- *Granularity*: size of tasks
- *Scheduling*: order of assignment of tasks
- *Mapping*: assignment of tasks to a PU
- *Load balancing:* the art of making the computation of multiple tasks end at the same time
- *Barrier*: a checkpoint at which all the parallel workers should wait for the last one.
- *Speedup*: time of the serial application/time of the parallel application
- *Efficiency*: Speedup/# of PUs
- *Race condition*: When the result of execution depends on sequence

  and/or timing of events. Result could be incorrect if this is not taken in consideration
- *Critical section*: Only one worker per time can enter.

Flynn's Taxonomy

Classification of computers describes four classes in both serial and parallel contexts:

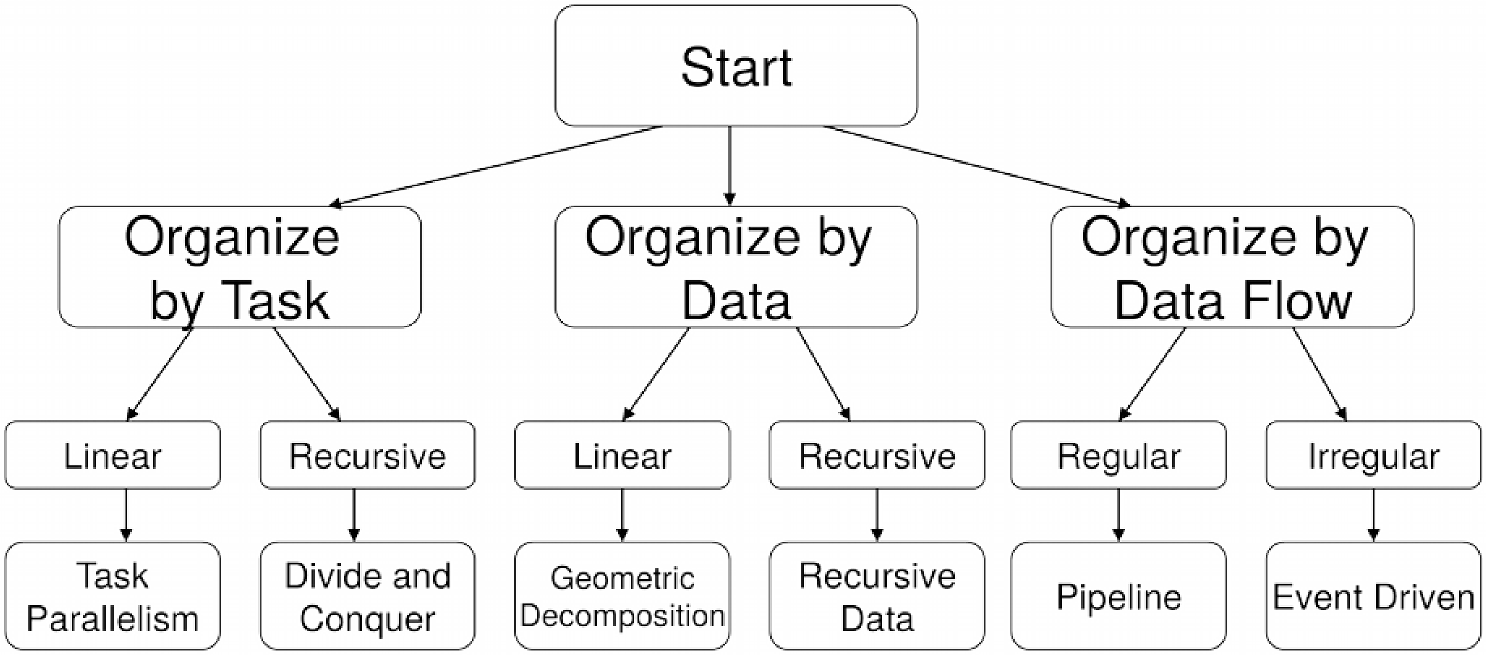
- **SISD** - *Single Instruction stream - Single Data stream*
  - A single processor computer that executes one stream of instructions on one set of data. Single-core processors belong to this class.
- **SIMD** - *Single Instruction Stream - Multiple Data stream*
  - A multiprocessor where each processing unit executes the same instruction stream as the others on its own set of data.
  - A set of processors shares the same control unit, and their execution differs only by the different data elements each processor operates on.

Flynn's Taxonomy (ctd.)

- **MISD** - *Multiple Instruction stream - Single Data stream*
  - Each processing element of the multiprocessor executes its own instructions, but operates on a shared data set.
- **MIMD** - *Multiple Instruction stream - Multiple Data stream*
  - Each processing element executes its own instruction stream on its own set of data.
- **SIMT** - *Single Instruction - Multiple Thread*
  - SIMD is combined with multithreading: we will see this with GPUs

Patterns for Parallel Programming

Parallel programming is not easy:
Apparently simple problems can hide many traps!



Mattson, Sanders, Massingill, *Patterns for Parallel Programming*

Reduce

Reduction is a very common pattern in parallel computing:

- Large input data structure distributed across many PU
- Each PU computes a tally of its input
- These tally values are combined to produce the final result

Examples:

- The sum of the elements of an array
- The maximum/minimum element of an array
- Find the first occurrence of x in an array

count number of 5s

```
array[N]
numberOf5 = 0
for i in [0,N[:
   if array[i] == 5
       numberOf5++
return numberOf5
```

```
numberOf5 = 0
nWorkers = 4
count5(array, workerId):
  beg = workerId*N/nWorkers
  end = beg + N/nWorkers
  for i in [beg,end[:
      if array[i] == 5:
        numberOf5++
```

Data Hazards

Threads within a process share the same address space but not their execution stack

Pro: Threads can communicate using shared memory

Cons: Data Hazards if threads are not synchronized

Data hazards usually occur when threads modify data in different points in the instruction pipeline and the order of reading and writing operation matters (data dependence)

- Read-After-Write (RAW)
- Write-After-Read (WAR)
- Write-After-Write (WAW)

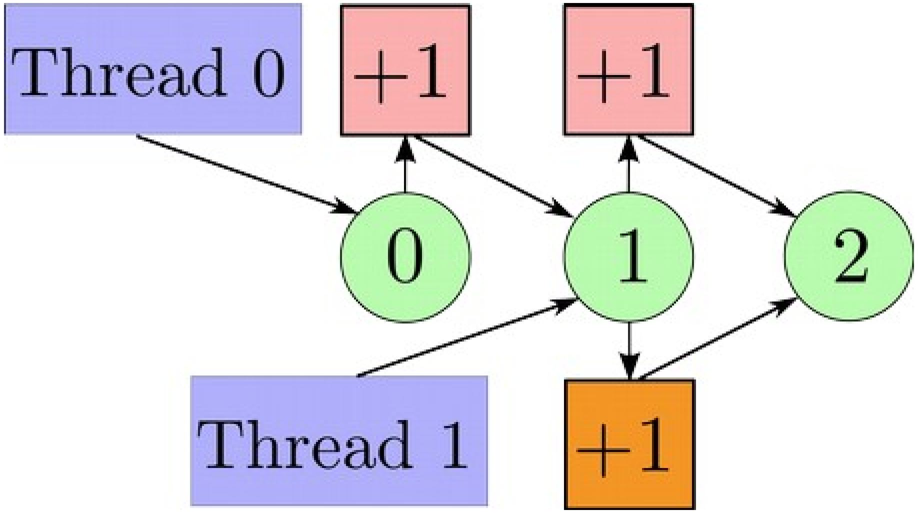
Data Hazards

Overlooking data hazards can lead to the corruption of the shared state (race condition)

Tricky to debug since the result depends on the timing between concurrent threads: unpredictable!

When a piece of code is clean of data hazards, it is said to be thread-safe.

The easiest ways to avoid conflicts in critical sections is to grant access one thread at a time: *mutex* (mutual exclusion)



count number of 5s

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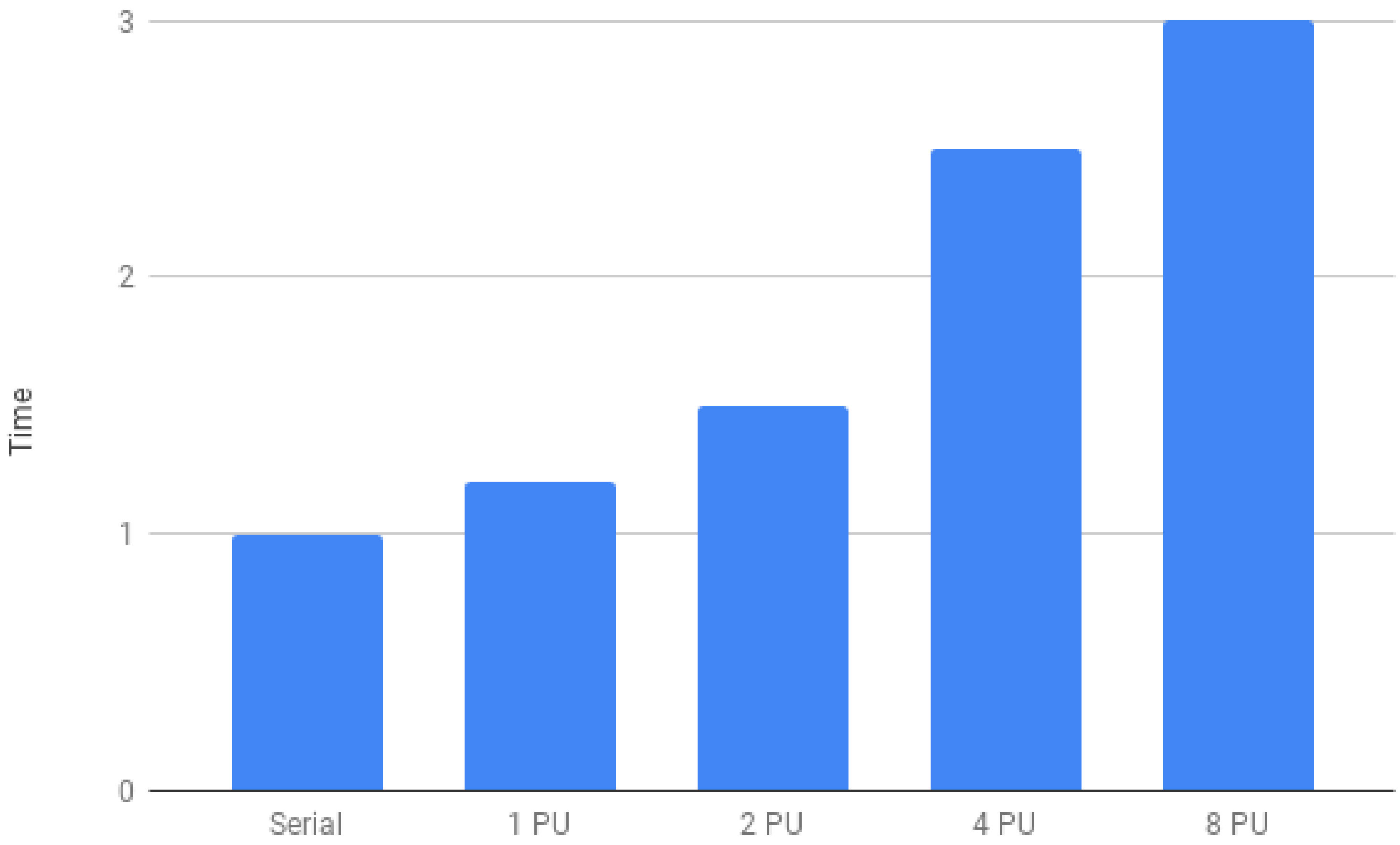
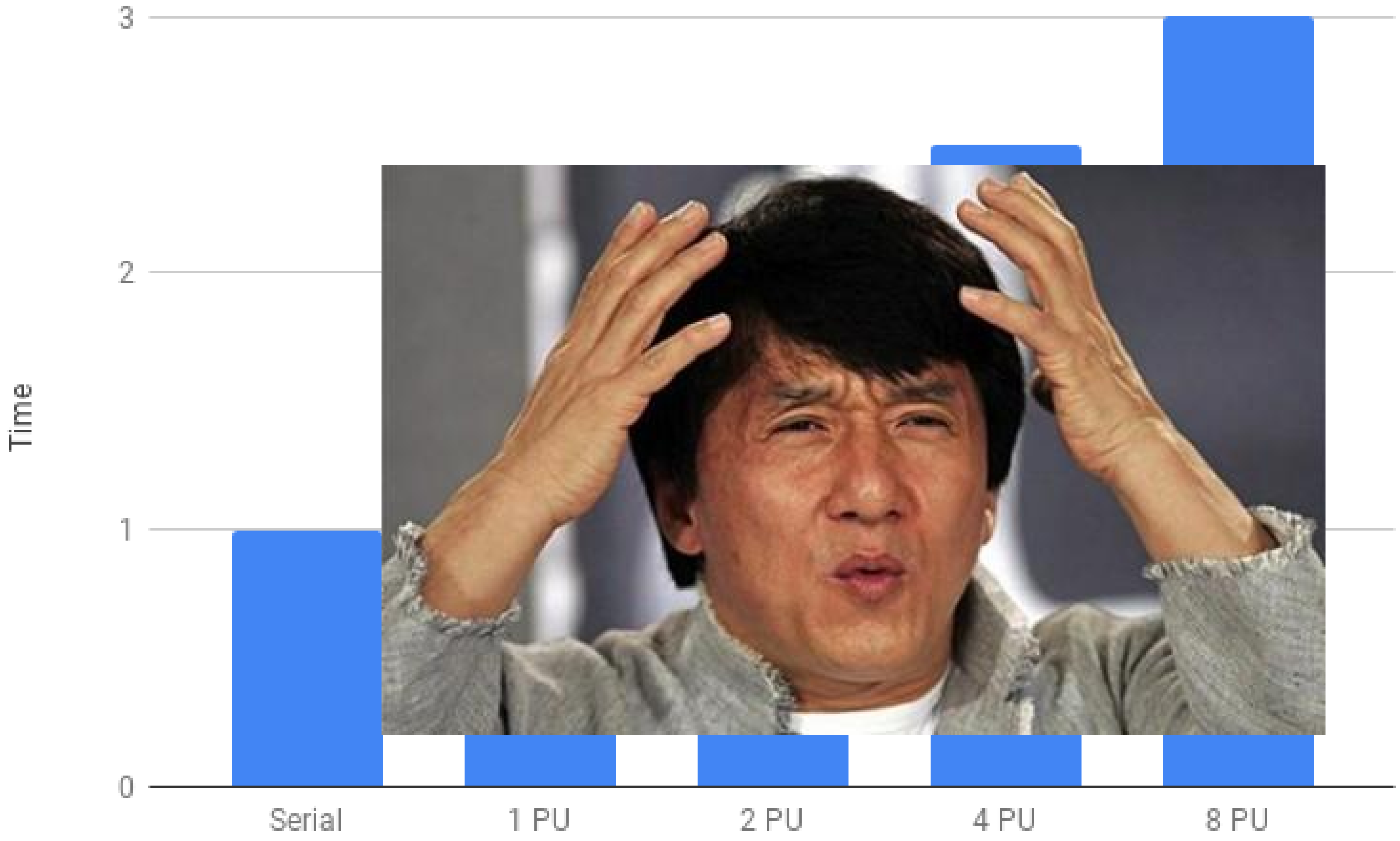
array[N]
numberOf5 = 0
for i in [0,N[:
   if array[i] == 5
       numberOf5++
return numberOf5
```

```
numberOf5 = 0
nWorkers = 4
count5(array, workerId):
  beg = workerId*N/nWorkers
  end = beg + N/nWorkers
  for i in [beg,end[:
      if array[i] == 5:
         lock()
         numberOf5++
         unlock()
```

Performance



Performance



Contention

- Conflicting Data Updates Cause Serialization and Delays:
- Massively parallel execution cannot afford serialization
- Contentions in updating critical data causes serialization

Mitigating contention

Contention can be mitigated with:

- Privatization
- Transformation of the access pattern

- Avoid frequent “phone calls” to the global memory and read/write the data locally as much as possible before updating the global value
- Make use of registers and shared memory for aggregating partial results
- Requires storage resources to keep copies of data structures

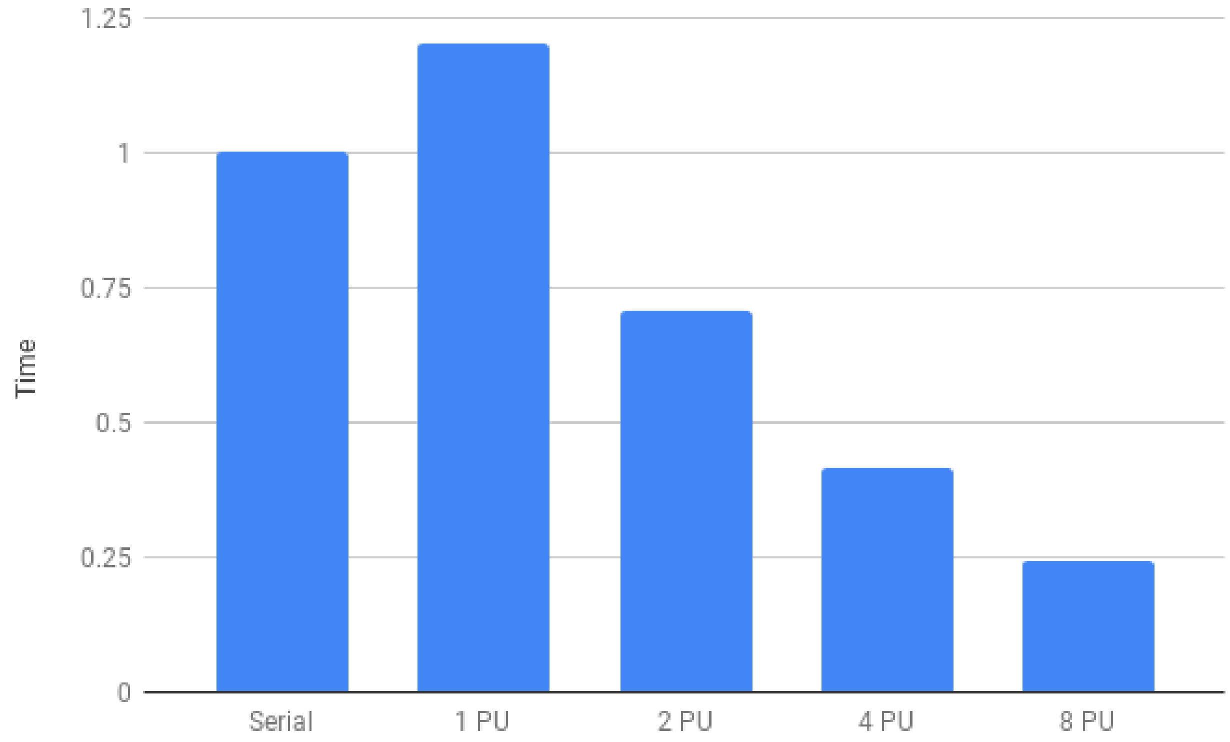
count number of 5s

```
array[N]
numberOf5 = 0
for i in [0,N[:
   if array[i] == 5
       numberOf5++
return numberOf5
```

```
numberOf5 = 0
nWorkers = 4
count5(array, workerId):
  privateResult = 0
  beg = workerId*N/nWorkers
  end = beg + N/nWorkers
  for i in [beg,end[:
       if array[i] == 5:
          privateResult++

   lock()
   numberOf5 += privateResult
   unlock()
```

Privatization



The T=8 version does not take half of the time w.r.t. T=4… Why?

Amdahl's Law

The maximum theoretical throughput is limited by Amdahl's Law:

- Every program contains a serial part
- Only one PU can execute the serial part
- The speedup using *p* PUs is given by

$$S(p) = \frac{T_s}{T_p}$$

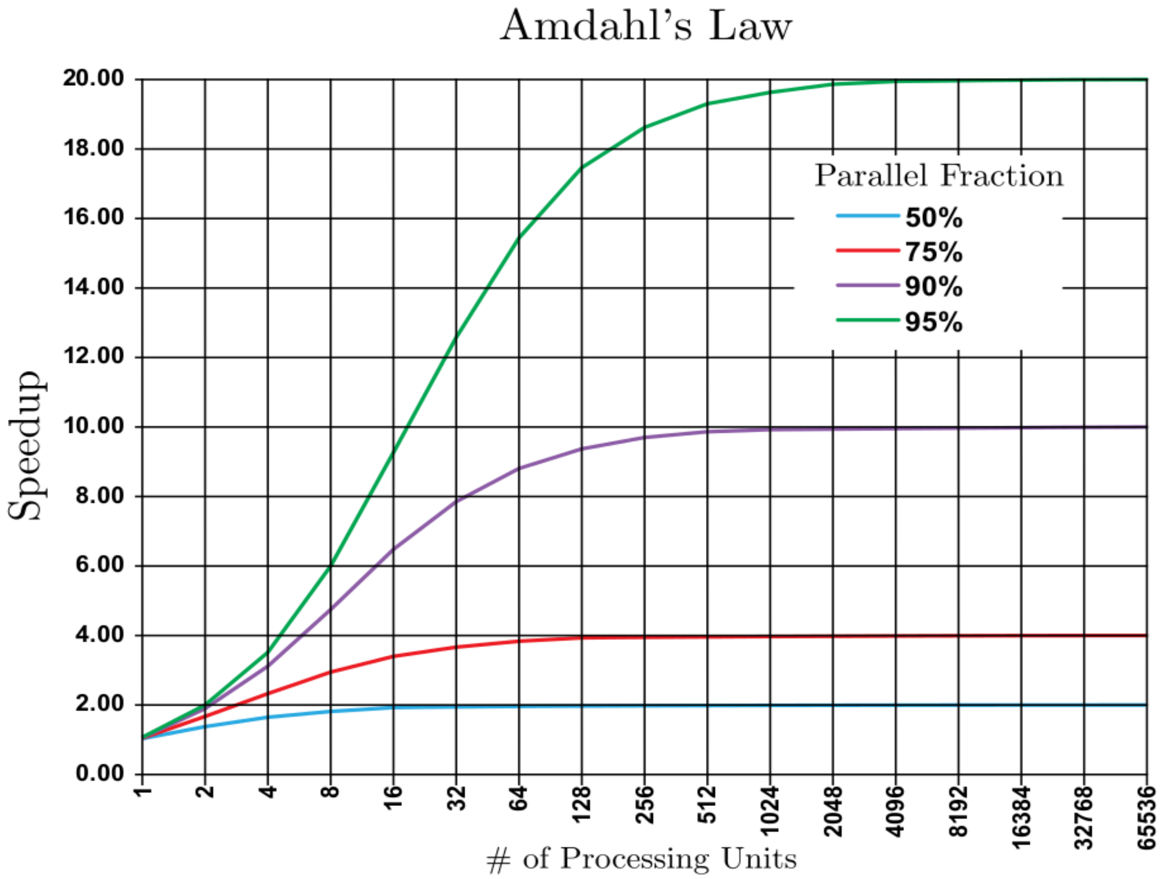
- If f is the fraction of the program that runs serially, the parallel execution time is given by:

$$T_p = fT_s + (1 - f)T_p = fT_s + \frac{(1 - f)t}{p}$$

Amdahl's Law (ctd.)

The speed-up becomes

$$S(p,f) = \frac{T_s}{fT_s + \frac{(1-f)t}{p}} \rightarrow \frac{1}{f} = S_{max}(f)$$



Mitigating Amdahl's Law: Gustafson's Law

- Amdahl's Law assumes that a problem can be split in a number of independent chunks *n* that can be processed in parallel and that this number is fixed
- Many times, the increase of the size of a problem does not correspond to a growth of the sequential part
  - increasing the size of the problem does not change the time spent executing the sequential part, and only affects the parallel portion
- Let *f (n)* be the sequential code fraction of the program

$$S(n) = f(n) + p[1 - f(n)]$$

- *f(n)* decreases to 0 when *n* approaches infinity.
- The maximum speedup is then given by:

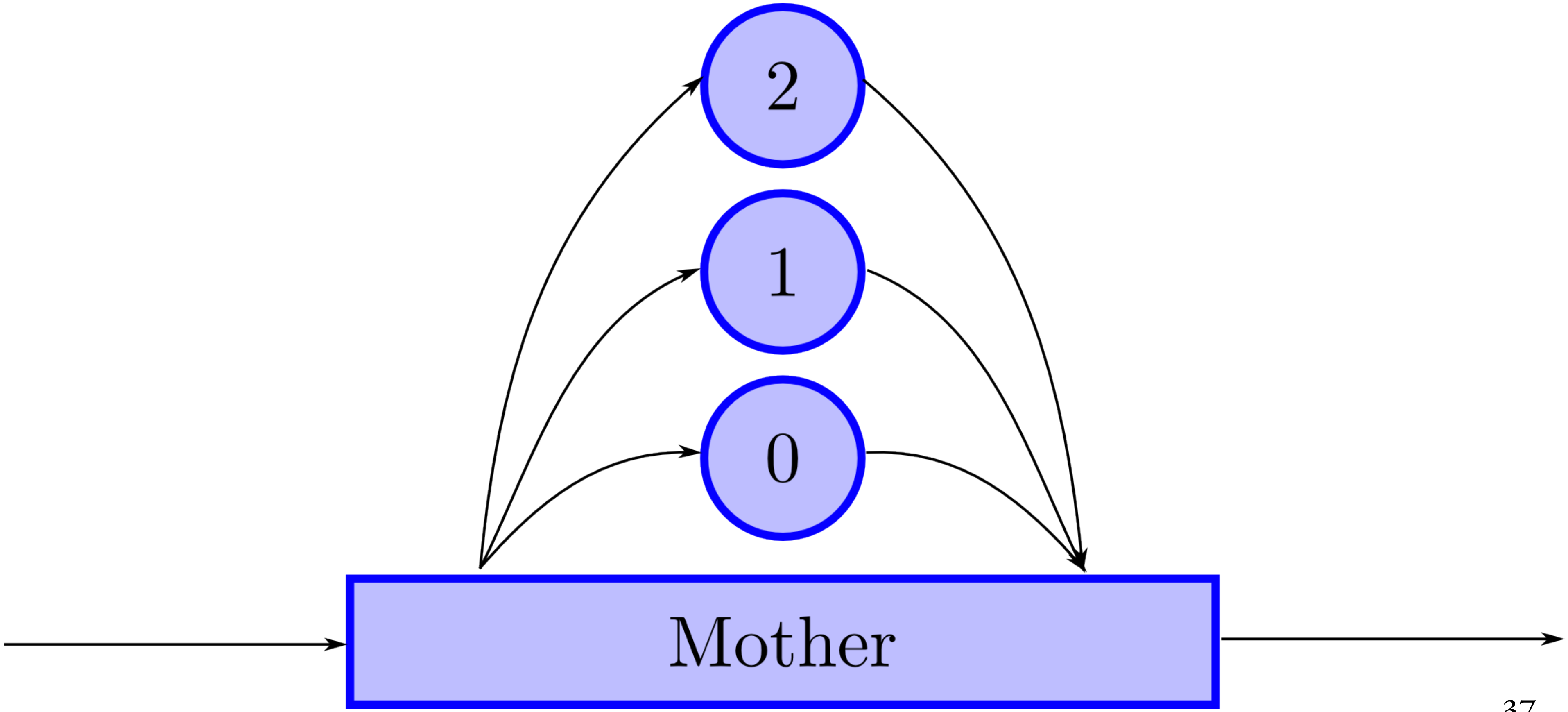
$$S_{max} \equiv \lim_{n \to \infty} S(n) = p$$

It's still worth to learn parallel computing: computations involving arbitrarily large data sets can be efficiently parallelized!

Mother-child parallelism

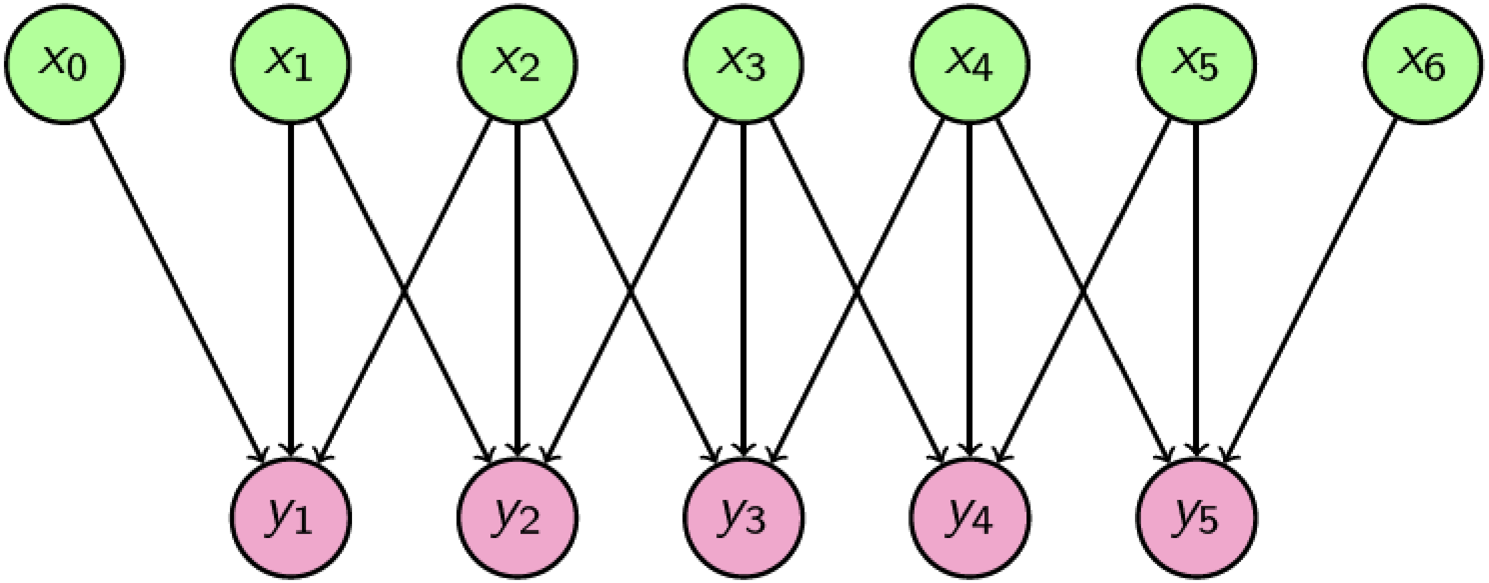
When thinking about possible parallel solutions:

- How to partition the problem
- How to share information



Data Partitioning

$$y_i = f_i(range(x_i, \delta))$$



Partitioning

- Static:
  - all information available before computation starts
  - use off-line algorithms to prepare before execution time
  - Run as pre-processor, can be serial, can be slow and expensive
- Dynamic:
  - information not known until runtime
  - work changes during computation (e.g. adaptive methods)
  - locality of objects can change (e.g. particles move)
  - use on-line algorithms to make decisions mid-execution
  - must run side-by-side with application
  - should be parallel, fast, scalable.
  - Incremental algorithm preferred (small changes in input result in small changes in partitions)

Why? In order to minimize idle time.

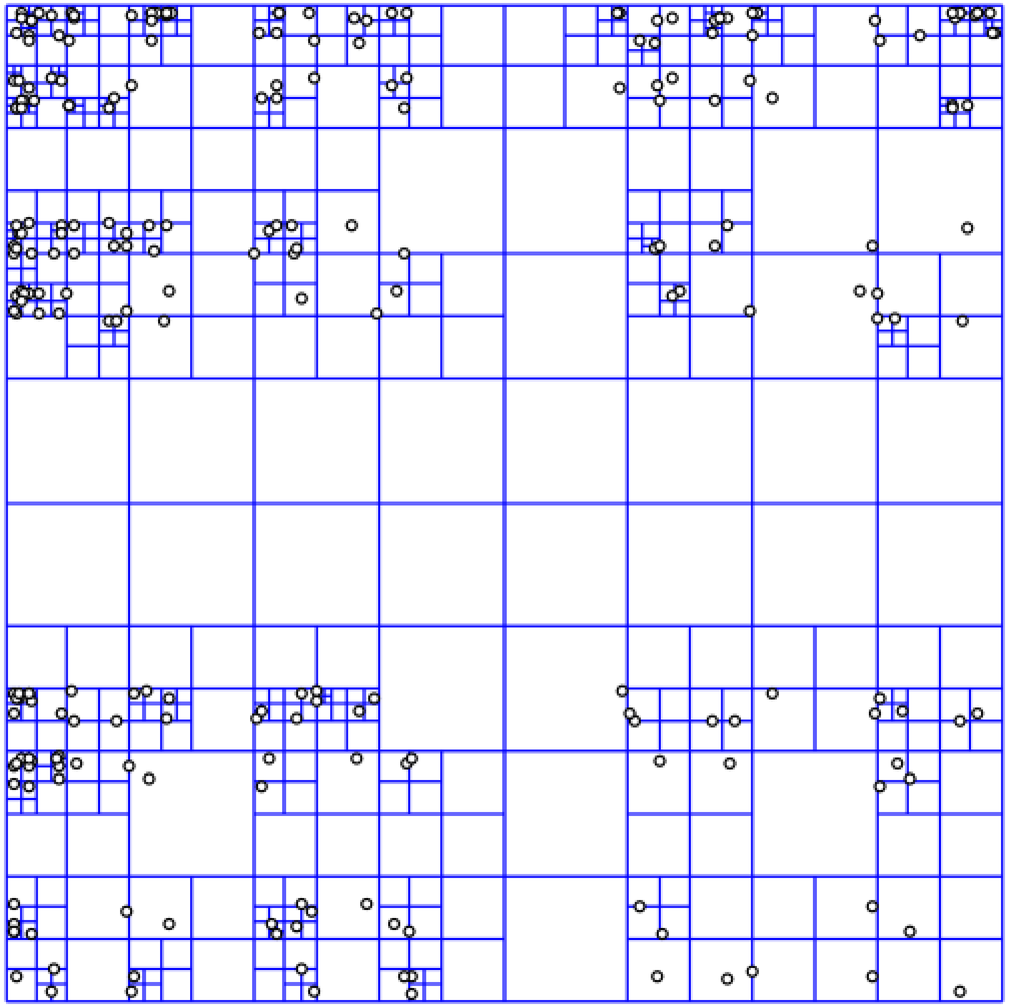
Load balancing

Sometimes dividing the input data in two does not mean that the load has been also divided in two.

Example:

Total load: 100

- If 5 workers take 20 each
  - Speedup 5
- If 1 worker takes 50
  - Speedup 2



Partitioning and Load Balancing

- Assignment of application data to processors for parallel computation
- Applied to grid points, elements, matrix rows, particles

Non-uniform data distributions

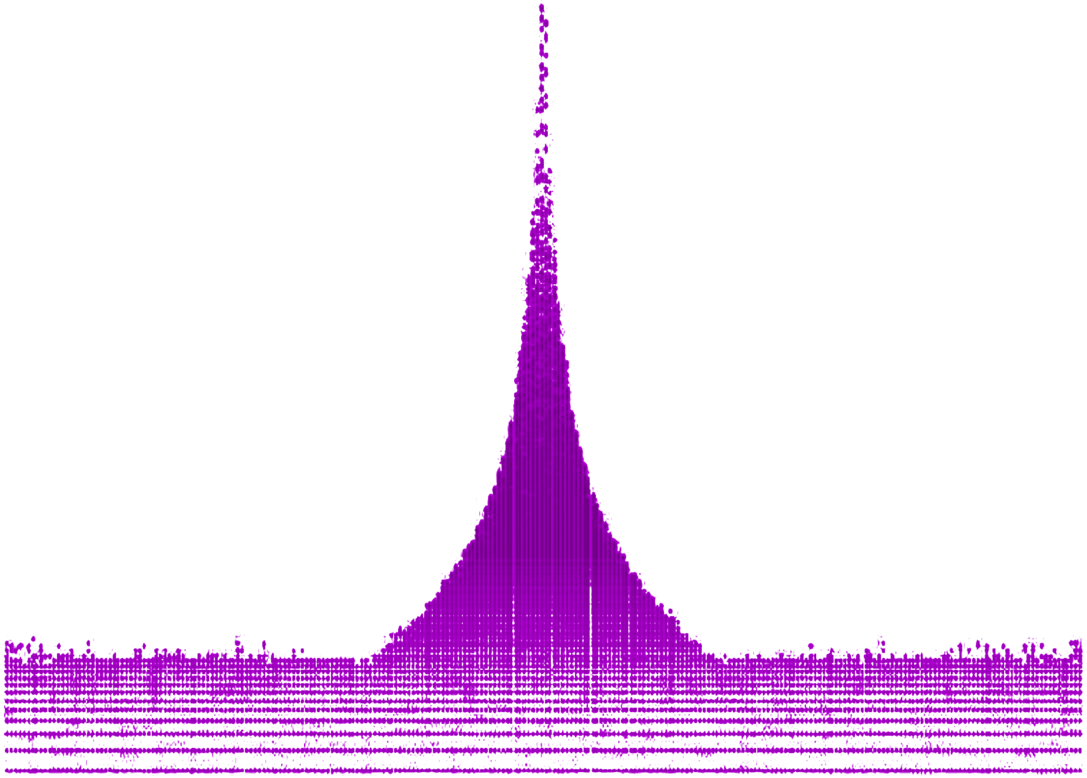
- Highly concentrated spatial

data areas

- Astronomy, medical imaging,

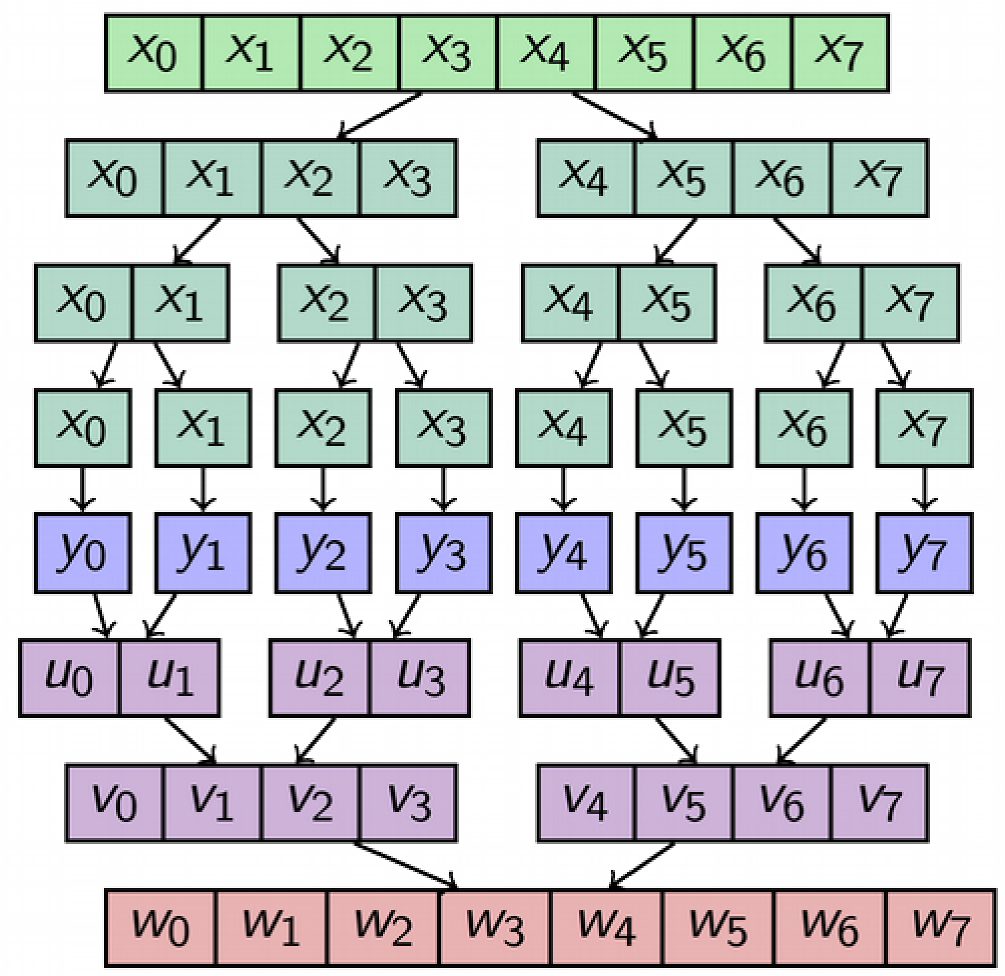
computer vision, rendering

If each thread processes the input data of a given spatial volume unit, some will do a lot more work than others



Divide et Impera

When you don't have any idea on how to approach the parallelization of a problem, try *Divide et Impera*



Load Imbalance

Sometimes load imbalance could also be caused by some underestimated consideration

- Example:

```
int N = 1000;
for(int i=0; i<N; ++i){
...
}
```

Load Imbalance

Sometimes load imbalance could also be caused by some underestimated consideration

- Example:

```
i_start = my_id * (N/num_threads);
i_end = i_start + (N/num_threads);
if (my_id == (num_threads-1))
  i_end = N;
for (i = i_start; i < i_end; i++) {
...
}
```

Load Imbalance

- The last thread executes the remainder

```
i_start = my_id * (N/num_threads);
i_end = i_start + (N/num_threads);
if (my_id == (num_threads-1))
   i_end = N;
for (i = i_start; i < i_end; i++) {
...
}
```

- If the number of threads is 32, each thread will execute 31 instructions
- The last thread will execute 8 more instructions
- Try to extrapolate to a bigger number of iterations and of threads!

Conclusion

Parallel computing becomes useful when:

- The solution to our problem takes too much time (Amdahl's Law)
- The size of our problem is big (Gustafson's Law)
- The solution of our problems is poor, we would like to have a better one

  Three steps to a better parallel software:

1. Restructure the mathematical formulation
2. Innovate at the algorithm and data structure level
3. Tune core software for the specific architecture

Think... think again

- Think about the problem you are trying to solve
- Understand the structure of the problem
- Apply mathematical techniques to find solution
- Map the problem to an algorithmic approach
- Plan the structure of computation
  - Be aware of in/dependence, interactions, bottlenecks
- Plan the organization of data
  - Be explicitly aware of locality, and minimize global data
- Finally, write some code! (this is the easy part)