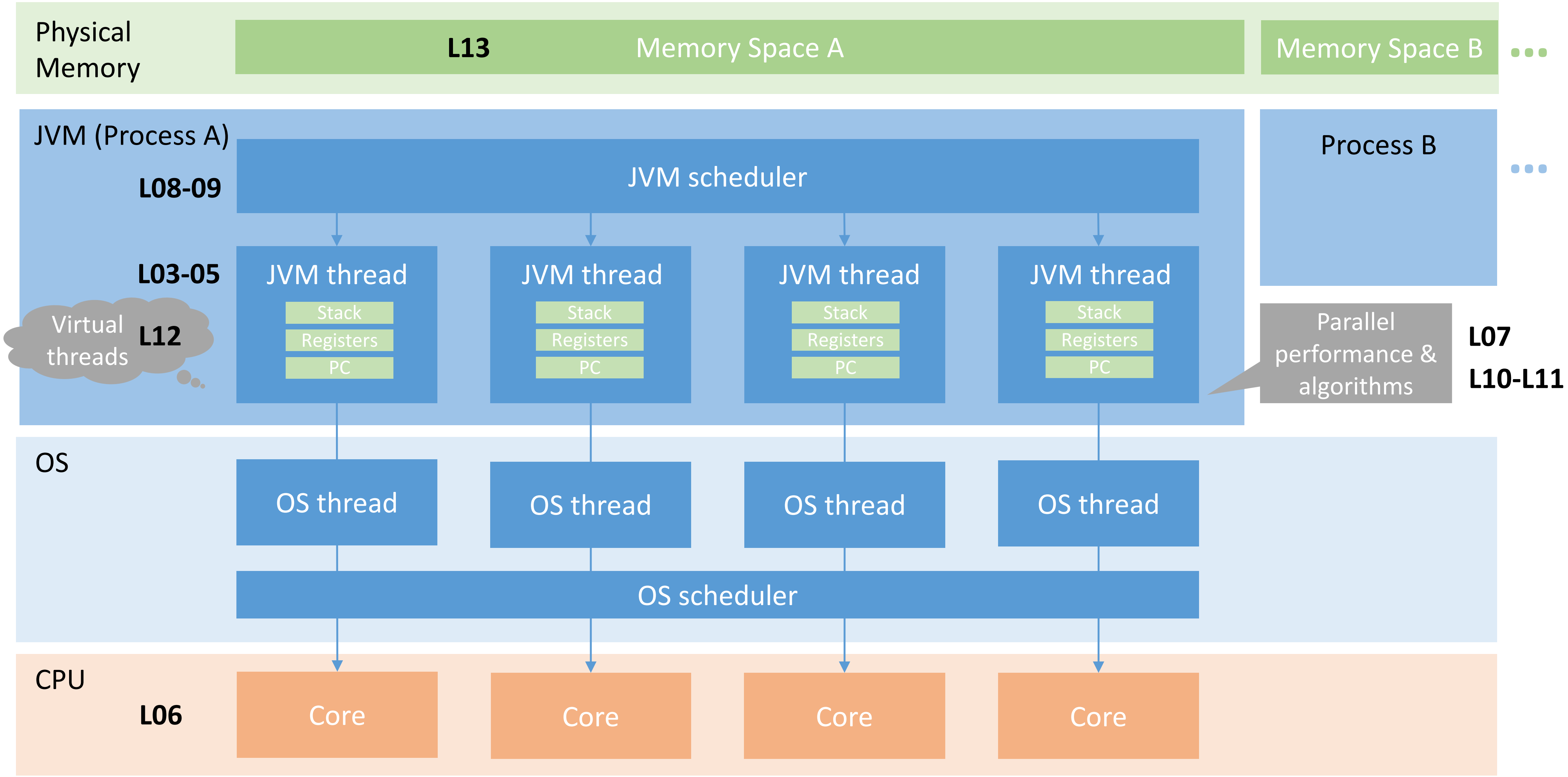
Parallel Programming

Basic Concepts in Parallelism

Big Picture (Part I)



Expressing Parallelism

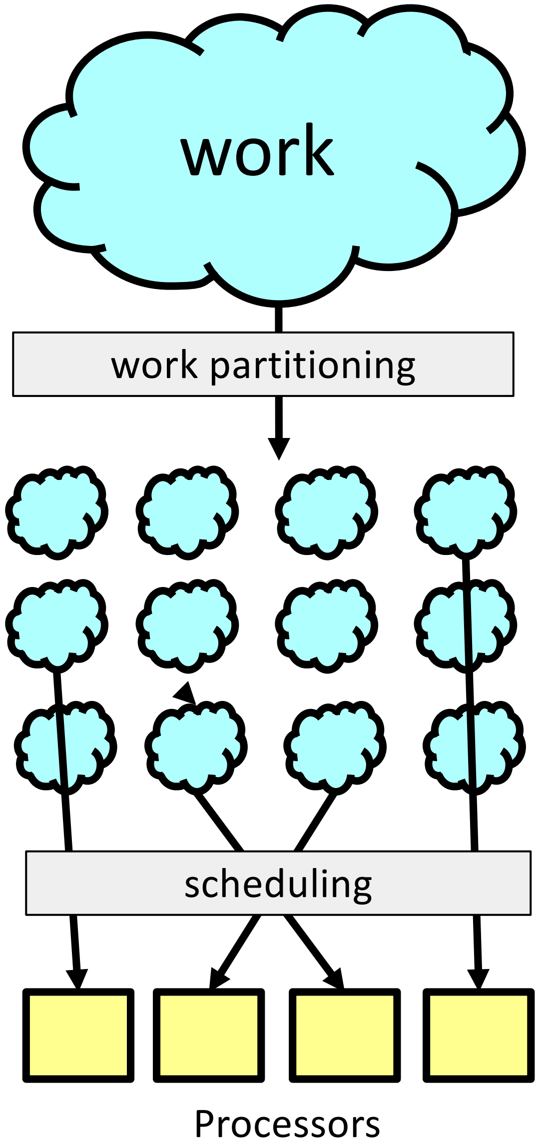
- Work partitioning
  - Split up work of a single program into **parallel tasks**

- Can be done:
  - Explicitly / Manually (**task/thread parallelism**)
    - User explicitly expresses tasks/threads
  - Implicit parallelism:
    - Done automatically by the system (e.g., in **data parallelism**)
    - User expresses an operation and the system does the rest

Work Partitioning & Scheduling

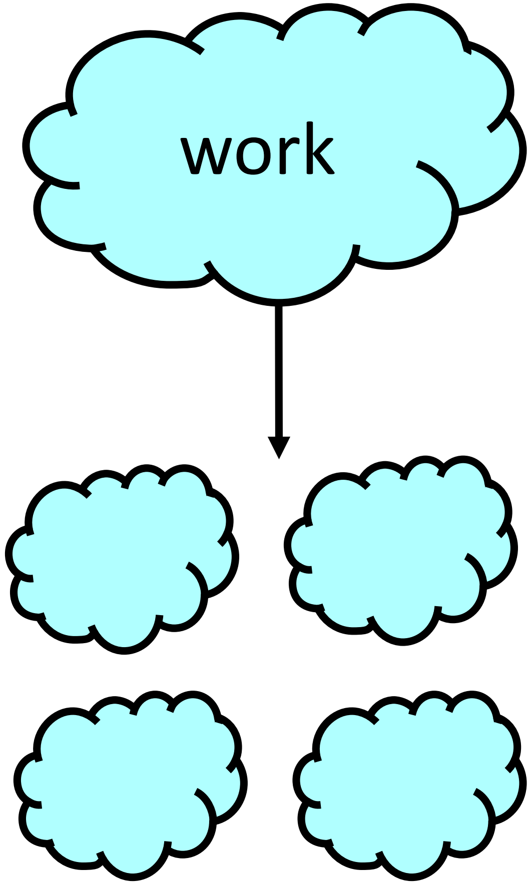
- **work partitioning**
  - **split up** work into **parallel tasks/threads**
  - (done by user)
  - A task is a unit of work
  - also called: **task/thread decomposition**
- **scheduling**
  - assign tasks to processors
  - (typically done by the system)
  - goal: <u>full utilization</u>

  (no processor is ever idle)

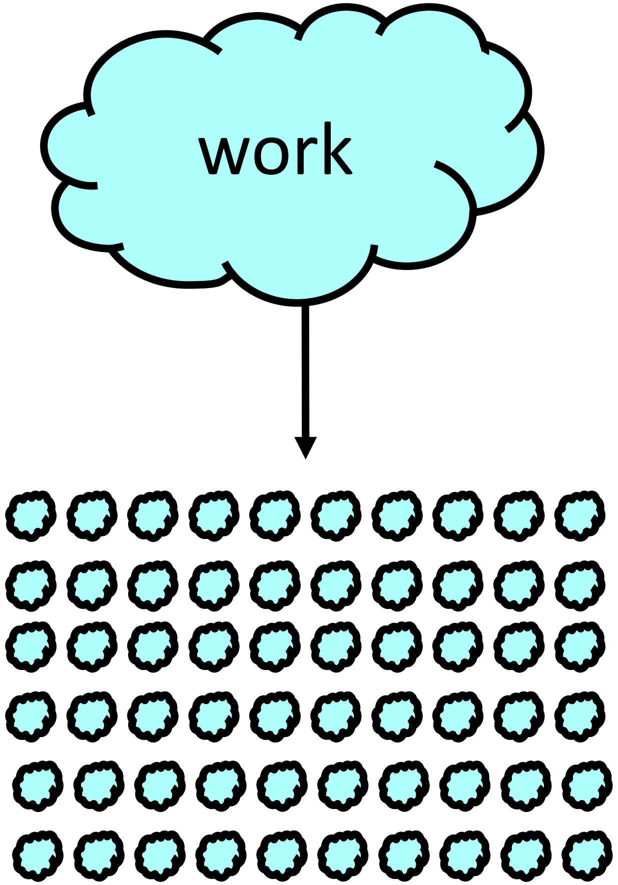


# of chunks should be larger than the # of processors

Task/Thread Granularity

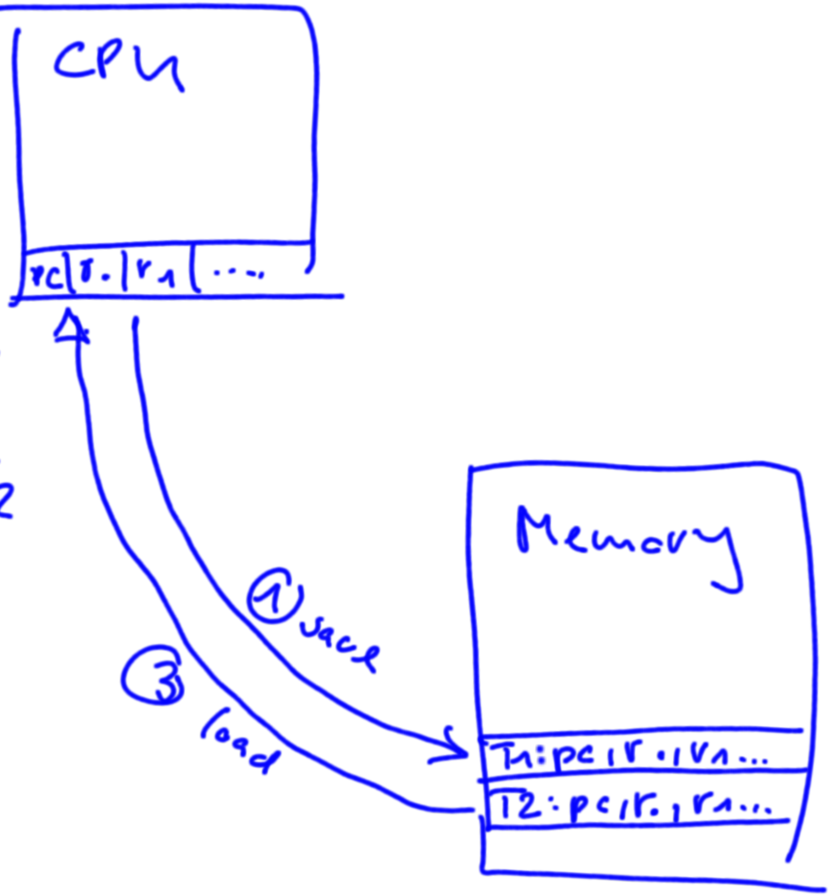


Coarse granularity



Fine granularity

1. save registers of T1
2. ask scheduler → T2
3. load T2



Coarse vs Fine granularity

- **Fine granularity:**
  - more portable

  (can be executed in machines with more processors)
  - better for scheduling
  - <u>but:</u> if scheduling overhead is comparable to a single task → overhead dominates

Task granularity guidelines

- As small as possible
- but, significantly bigger than scheduling overhead
  - system designers strive to make overheads small

Scalability

An overloaded concept: e.g., how well a system reacts to increased load, for example, clients in a server

In parallel programming:

- speedup when we increase processors
- what will happen if processors → ∞
- a program scales linearly → linear speedup

Parallel Performance

Sequential execution time: $\mathbf{T_1}$

Execution time $\mathbf{T_p}$ on $\mathbf{p}$ CPUs

- $\mathbf{T_p = T_1 / p}$ (perfection)
- $\mathbf{T_p > T_1 / p}$ (performance loss, what normally happens)
- $\mathbf{T_p < T_1 / p}$ (sorcery!)

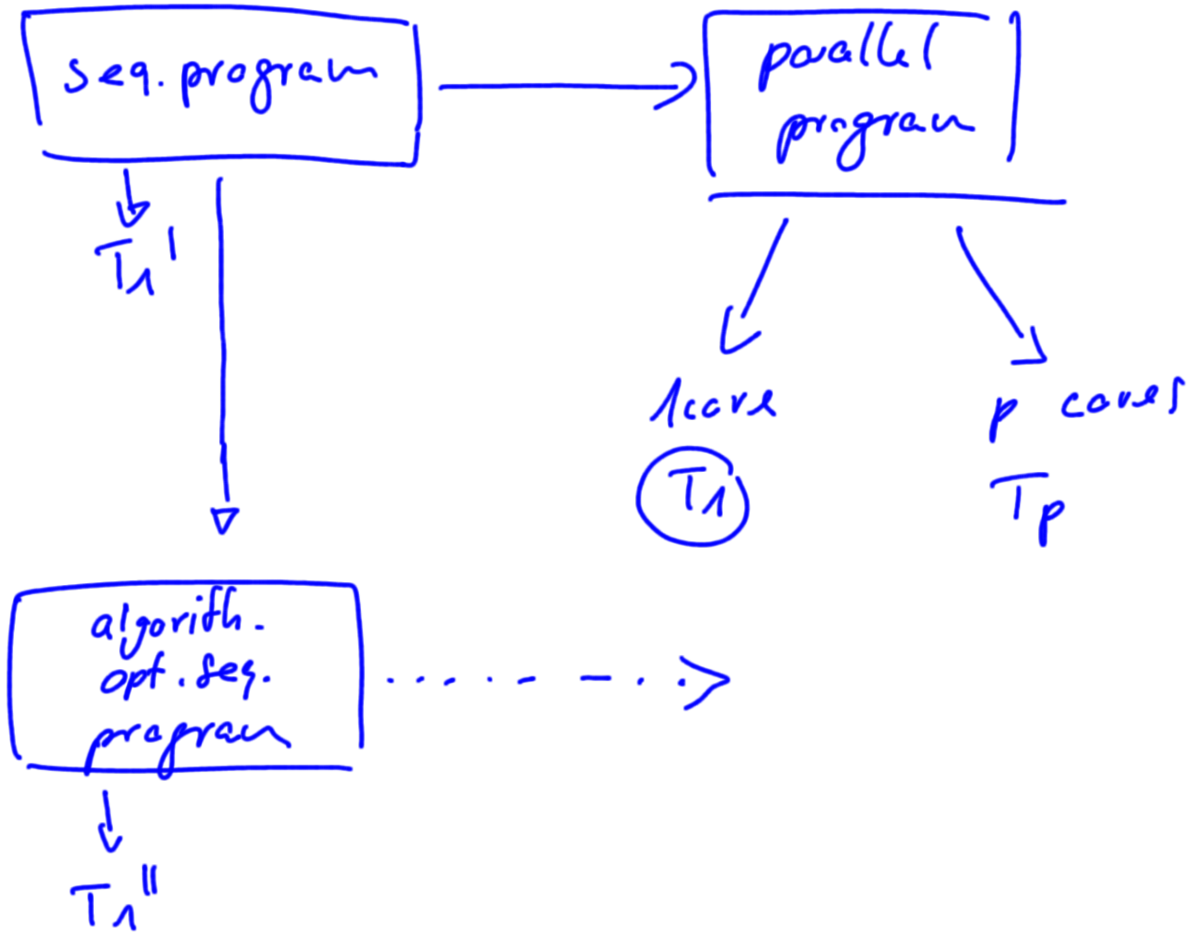
(parallel) Speedup

(parallel) speedup S_p on **p** CPUs:

$$S_p = T_1 / T_p$$

- $S_p = p$ → linear speedup (perfection)
- $S_p < p$ → sub-linear speedup (performance loss)
- $S_p > p$ → super-linear speedup (sorcery!)

- **Efficiency: S_p / p**

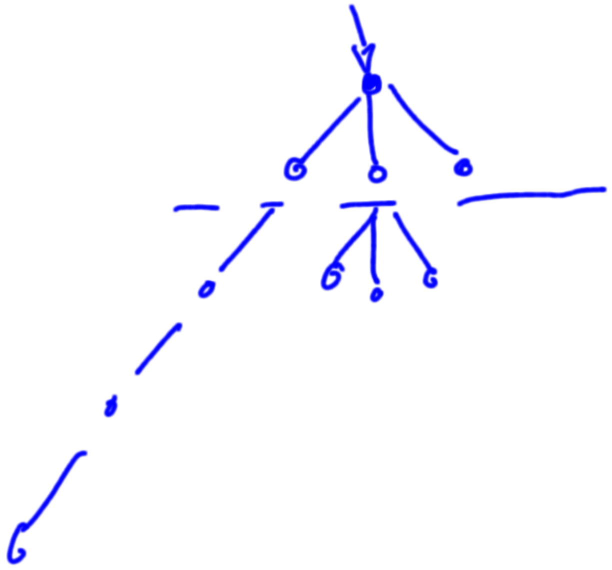


$$T_1'' \ll T_1' < T_1$$

what is the baseline?

$$S_p = \frac{T_1}{T_p}$$

$S_p \leq 1$



$S_p >> 1$

$$S_p = \frac{T_1}{T_p}$$

Efficiency: $\frac{S_p}{p} = 1 \hat{=} 100\%$ (linear)

$P = 1000$ cores

$\rightarrow S_p = 100$

$\rightarrow E = \frac{100}{1000} = 0.1 \Rightarrow 10\%$

Absolute versus Relative Speed-up

Relative speedup (Efficiency):

relative improvement from using P execution units.

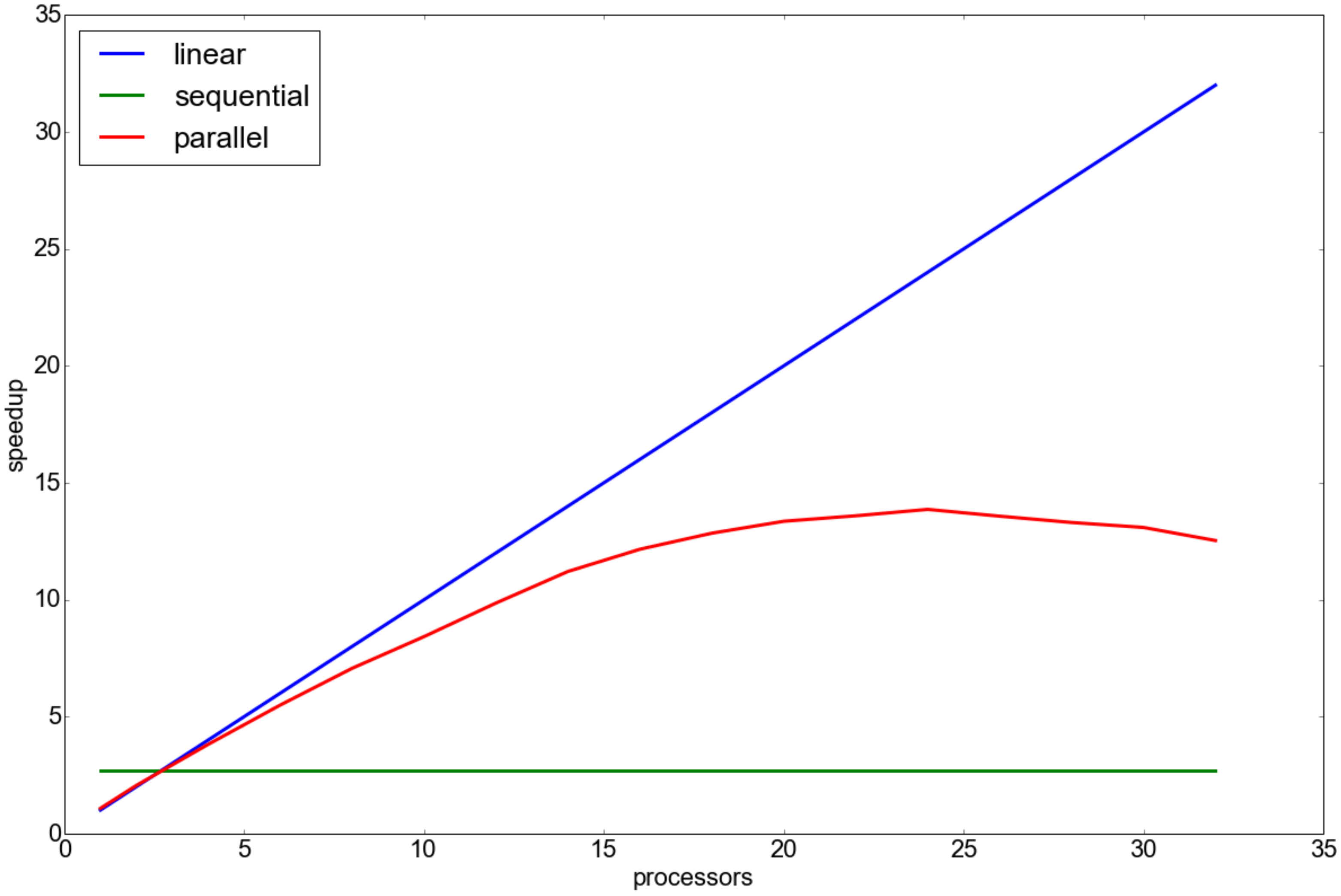
(Baseline: serialization of the parallel algorithm).

Sometimes there is a better serial algorithm that does not parallelize well.

In these cases it is fairer to use that algorithm for T_1 (absolute speedup).

Using an unnecessarily poor baseline artificially inflates speedup and efficiency.

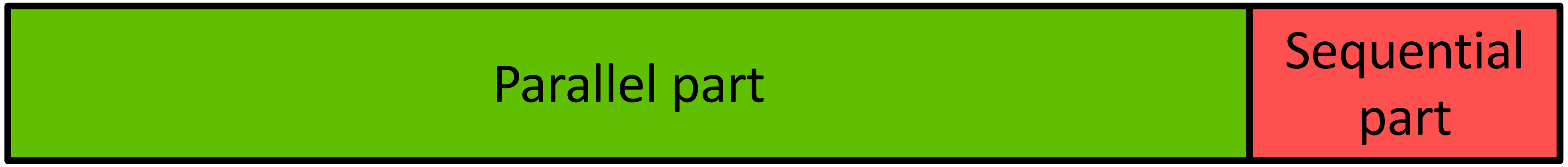
(parallel) speedup graph example



why $S_p < p$?

- Programs may not contain enough parallelism
  - e.g., some parts of program might be sequential
- overheads introduced by parallelization
  - typically associated with synchronization
- architectural limitations
  - e.g., memory contention

Question:



Parallel program:

- sequential part: 20%
- parallel part: 80% (assume it scales linearly)
- $T_1 = 10$

What is T_8 ? What is the speedup S_8 ?

80% P	20% S

$T_1 = 10$

Seq: $10 \cdot 0.2 = 2$

parallel: $10 \cdot 0.8 = 8$

$p = 8$

T_8 ?

$$T_8 = T_{seq} + T_{par}$$

$$= 10 \cdot 0.2 + \frac{10 \cdot 0.8}{8}$$

$$= 2 + 1$$

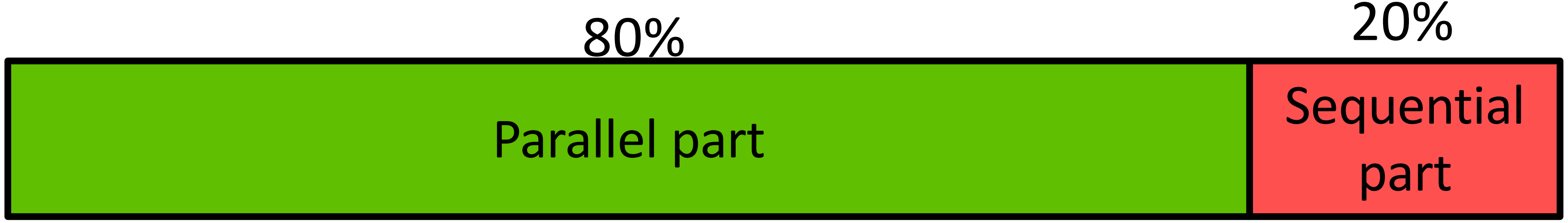
$$T_8 = 3$$

$$S_8 = \frac{T_1}{T_8} = \frac{10}{3} = 3.\overline{3}$$

$$E_8 = \frac{S_8}{p} = \frac{3.\overline{3}}{8} \approx 40\%$$

p	T_1	T_p	$S_p = \frac{T_1}{T_p}$	$\epsilon = \frac{S_p}{p}$
1	10	10	1	1
2	10	$2 + \frac{8}{2} = 6$	$\frac{10}{6} = 1.\overline{6}$	$\frac{1.\overline{6}}{2} = 83\%$
3	10	$2 + \frac{8}{3} = 4.\overline{6}$	$\frac{10}{4.6} \approx 2.1$	$\frac{2.1}{3} \approx 71\%$
$\vdots$				$\vdots$
8	10	3	$3.\overline{3}$	40%

Answer:



- $T_1 = 10$
- $T_8 = 3$
- $S_8 = T_1/T_8 = 10/3 = 3.33$

Amdahl’s Law

…the effort expended on achieving high parallel processing rates is wasted unless it is accompanied by achievements in sequential processing rates of very nearly the same magnitude.

— Gene Amdahl

Amdahl's Law – Ingredients

Execution time T_1 of a program falls into two categories:

- Time spent doing non-parallelizable serial work
- Time spent doing parallelizable work

Call these W_{ser} and W_{par} respectively

Amdahl's Law – Ingredients

Given P workers available to do parallelizable work, the times for sequential execution and parallel execution are:

$$T_1 = W_{ser} + W_{par}$$

And this gives a bound on speed-up:

$$T_p \geq W_{ser} + \frac{W_{par}}{P}$$

Amdahl’s Law

Plugging these relations into the definition of speedup yields Amdahl's Law:

$$S_p \leq \frac{W_{ser} + W_{par}}{W_{ser} + \frac{W_{par}}{P}}$$

Amdahl's Law - Corollary

$$S_p \leq \frac{W_{ser} + W_{par}}{W_{ser} + \frac{W_{par}}{P}}$$

If $\boldsymbol{f}$ is the non-parallelizable serial fractions of the total work, then the following equalities hold:

$$W_{ser} = \boldsymbol{f} T_1,$$
$$W_{par} = (1 - \boldsymbol{f}) T_1$$

which gives:

$$S_p \leq \frac{1}{\boldsymbol{f} + \frac{1 - \boldsymbol{f}}{P}}$$

$$S_p \le \frac{T_1}{T_p} = \frac{W_{ser} + W_{par}}{W_{ser} + \frac{W_{par}}{p}} = \frac{f\cancel{T_1} + (1-f)\cancel{T_1}}{f\cancel{T_1} + \frac{(1-f)\cancel{T_1}}{p}}$$

$$= \frac{1}{f + \frac{(1-f)}{p}} \qquad p \to \infty ?$$

50% seriell

$f = 0.5$

$$S_\infty \le \frac{1}{0.5} = 2\times$$

$$\boxed{50\%\, s \;\Big|\; \underbrace{50\%\, p}_{\downarrow \; 0}}$$

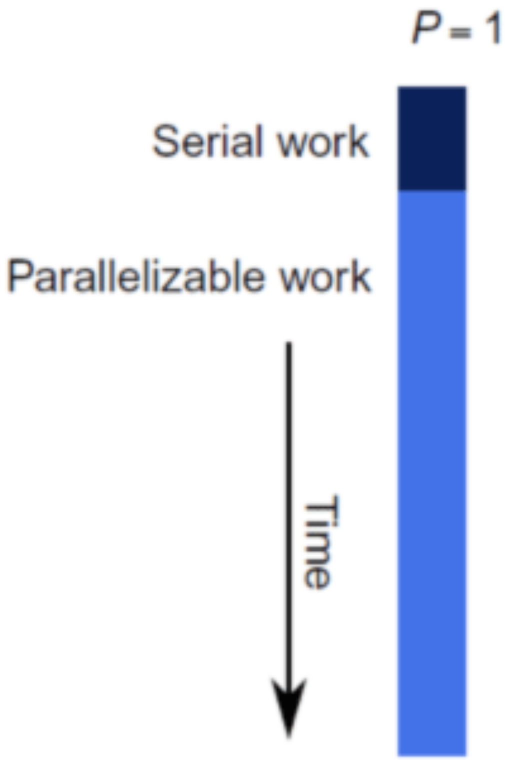
$f = 0.1$

$$S_\infty \le \frac{1}{0.1} = 10\times$$

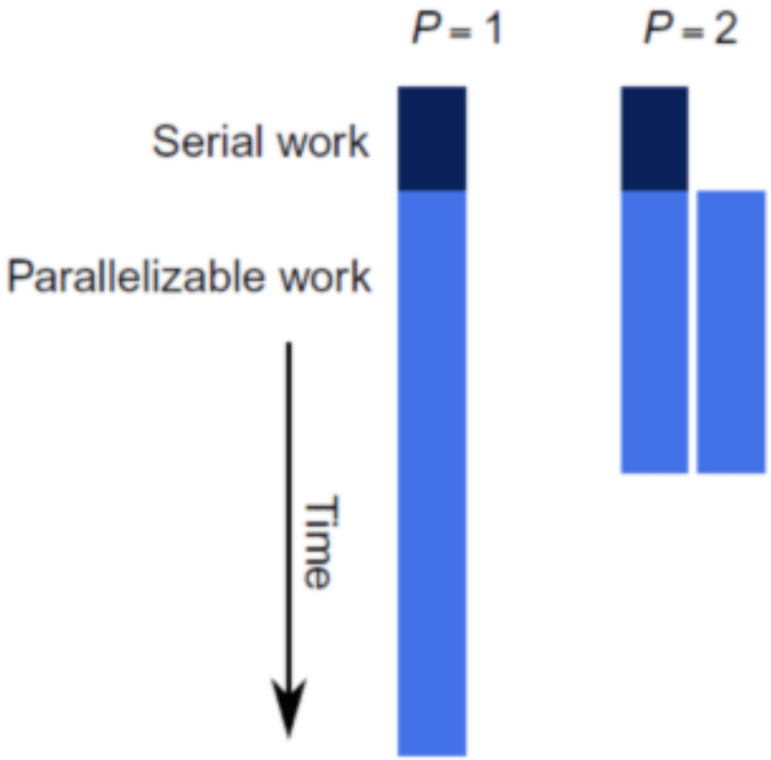
What happens if we have infinite workers?

$$S_{\infty} \leq \frac{1}{f}$$

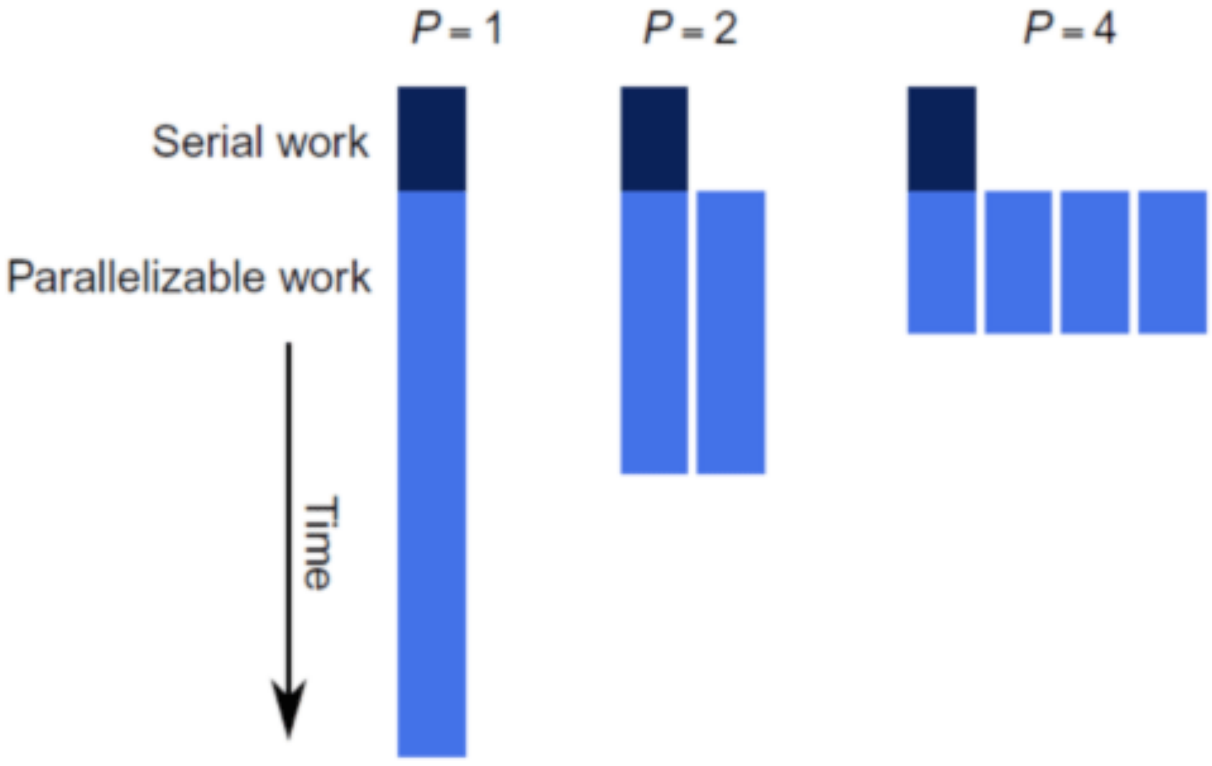
Amdahl’s Law Illustrated



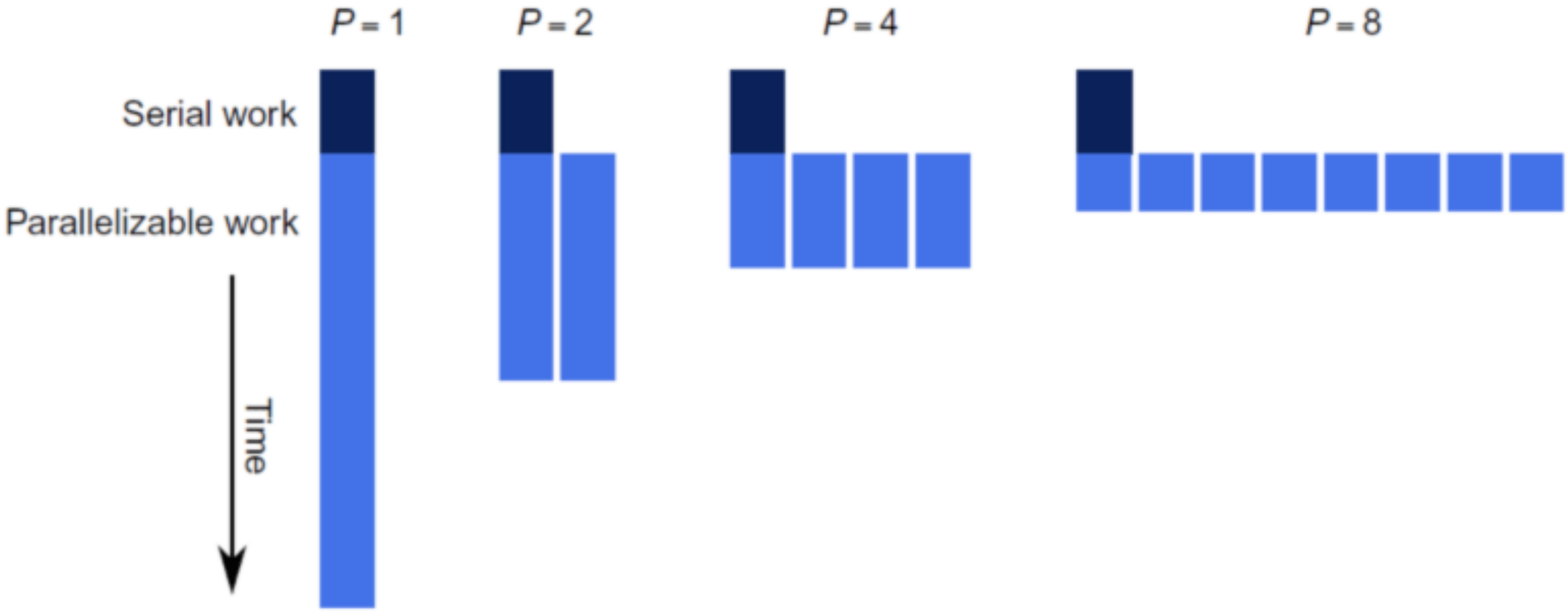
Amdahl's Law Illustrated



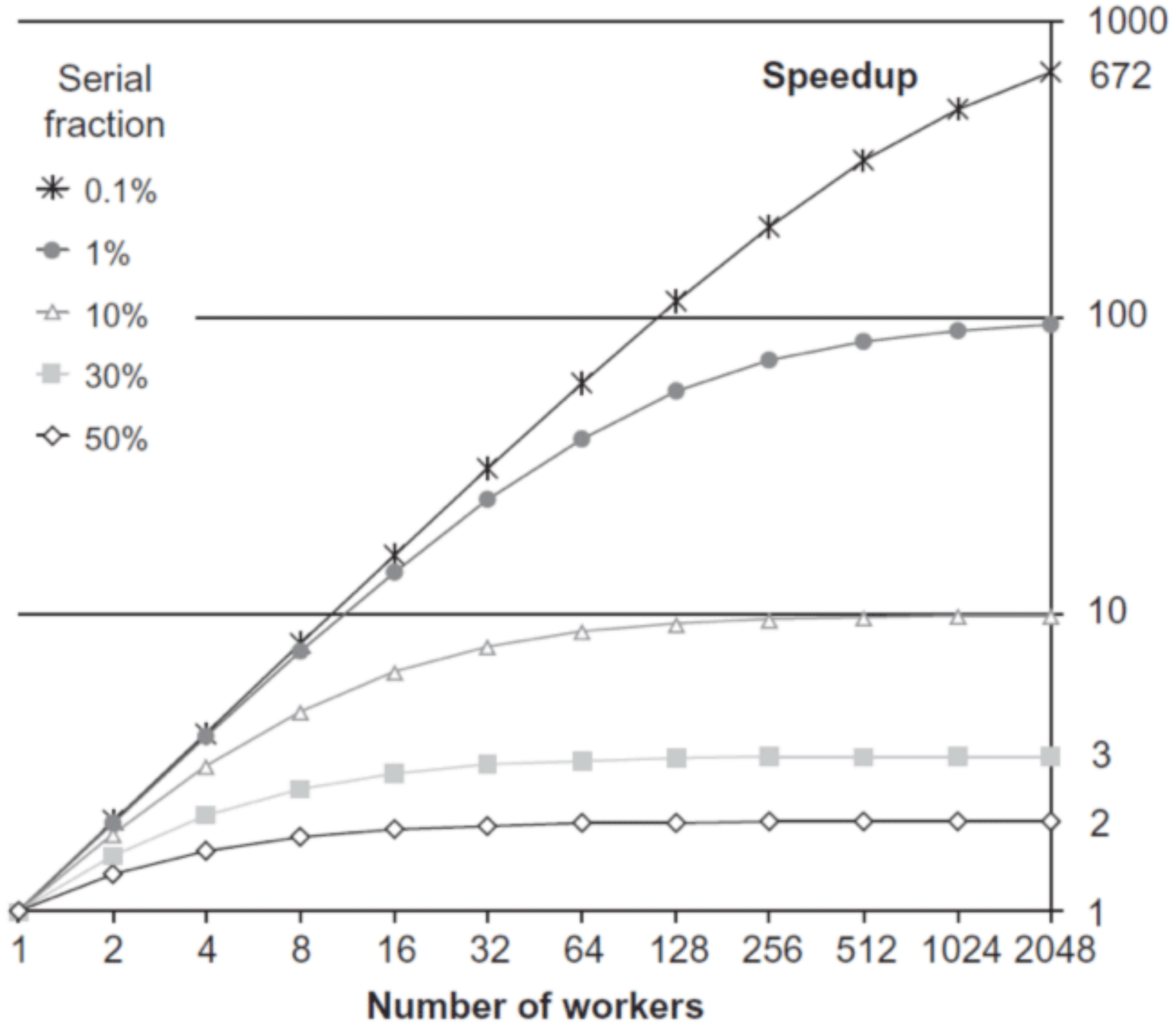
Amdahl’s Law Illustrated



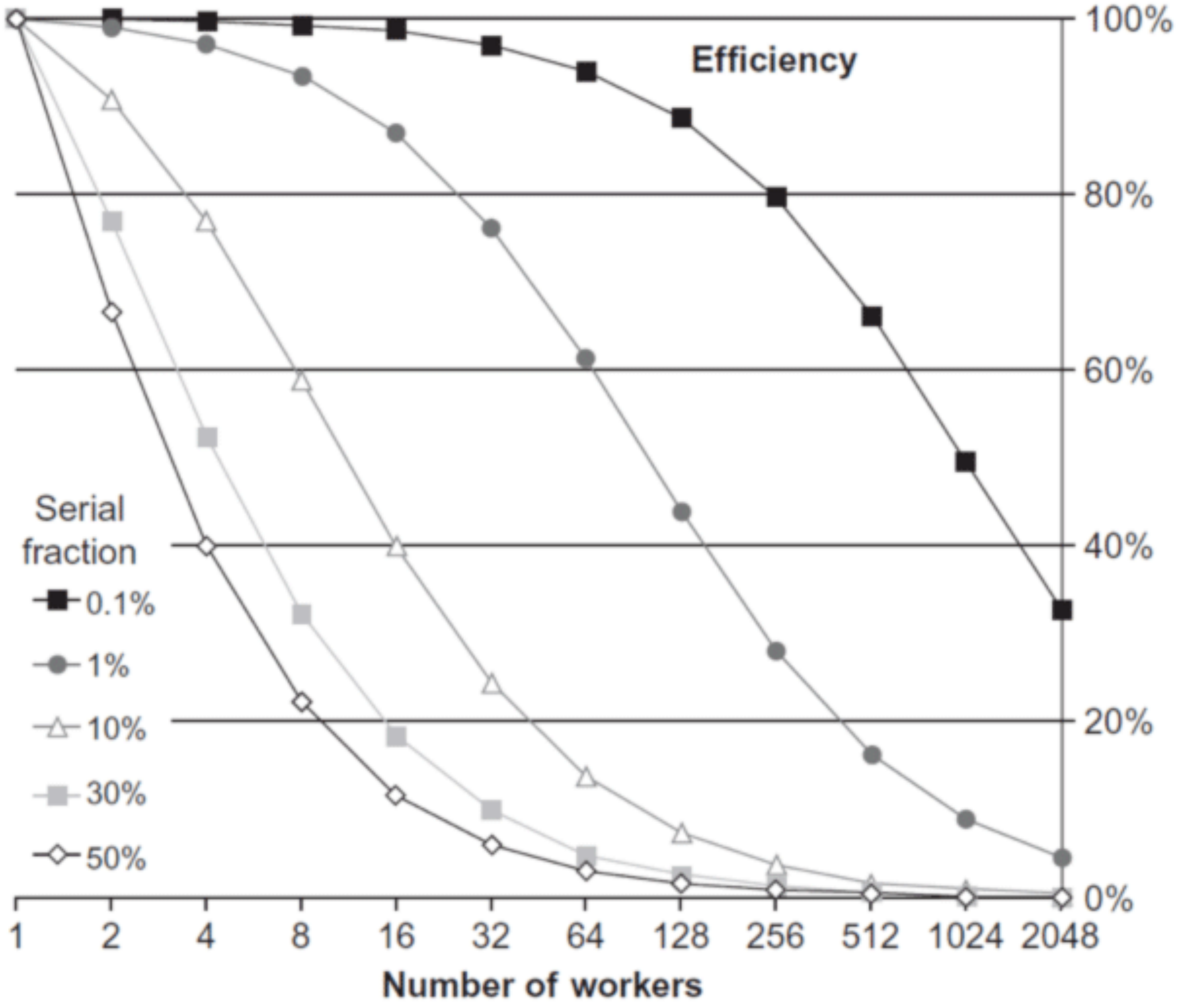
Amdahl's Law Illustrated



Speedup


Serial fraction
0.1%
1%
10%
30%
50%
Speedup
1000
672
100
10
3
2
1
1
2
4
8
16
32
64
128
256
512
1024
2048
Number of workers

Efficiency



Efficiency
100%
80%
60%
40%
20%
0%
Serial fraction
0.1%
1%
10%
30%
50%
1 2 4 8 16 32 64 128 256 512 1024 2048
Number of workers

Remarks about Amdahl's Law

- It concerns ***maximum speedup*** (Amdahl was an optimist *(or pessimist?)*)
  - architectural constraints will make factors worse
- But his law is ***mostly bad news*** (as it puts a limit on scalability)

- takeaway: **all non-parallel parts of a program (no matter how small) can cause problems**

- Amdahl’s law shows that efforts required to further reduce the fraction of the code that is sequential may pay off in large performance gains.

- Hardware that achieves even a small decrease in the percent of things executed sequentially may be considerably more efficient

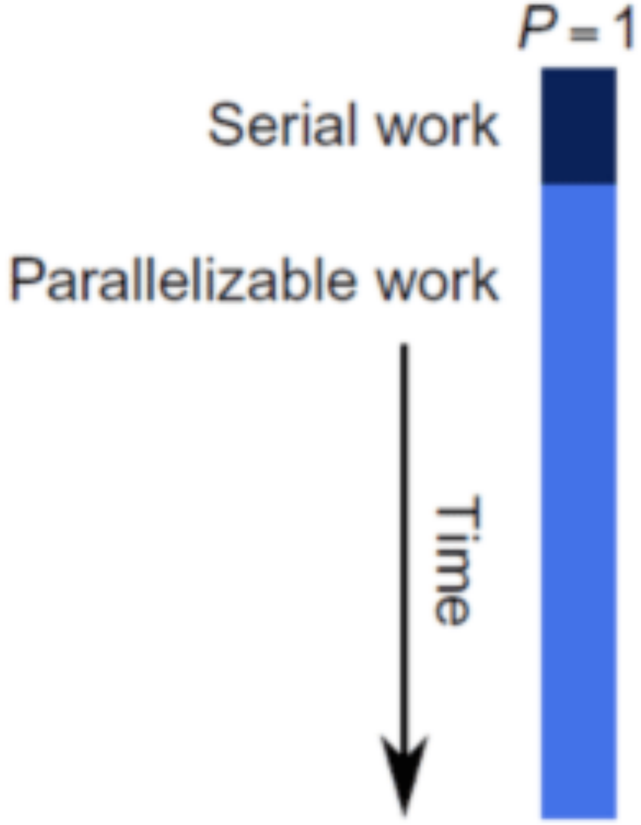
Gustafson’s Law

- An alternative (optimistic) view to Amdahl's Law

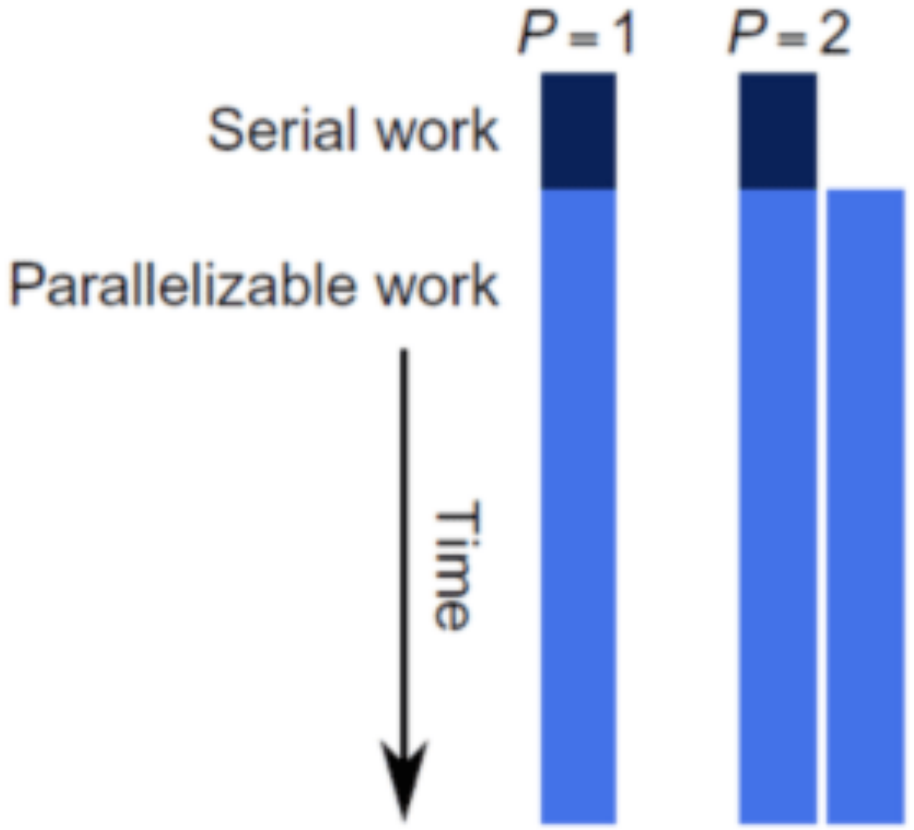
Observations:

- consider problem size
- run-time, not problem size, is constant
- more processors allows to solve larger problems in the same time
- parallel part of a program scales with the problem size

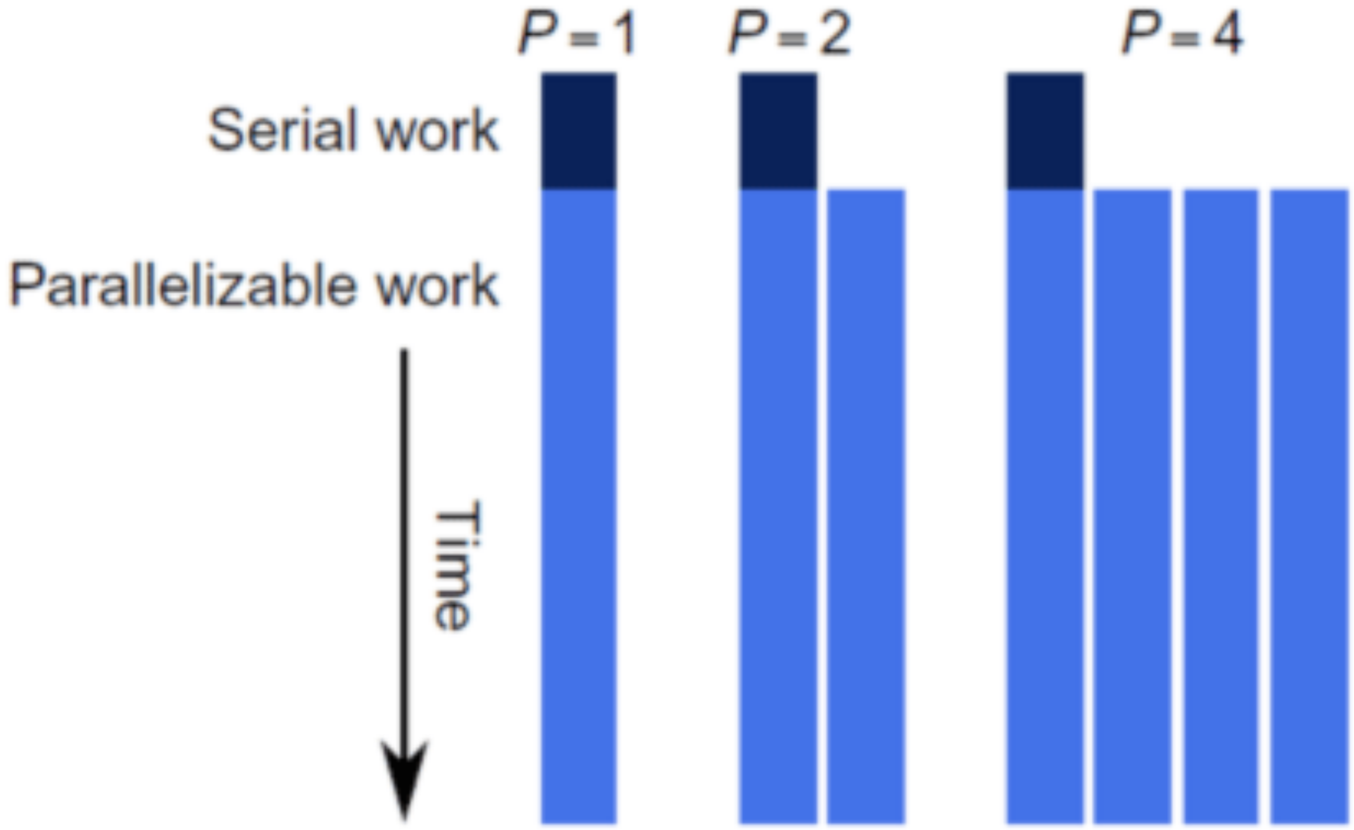
Gustafson's Law



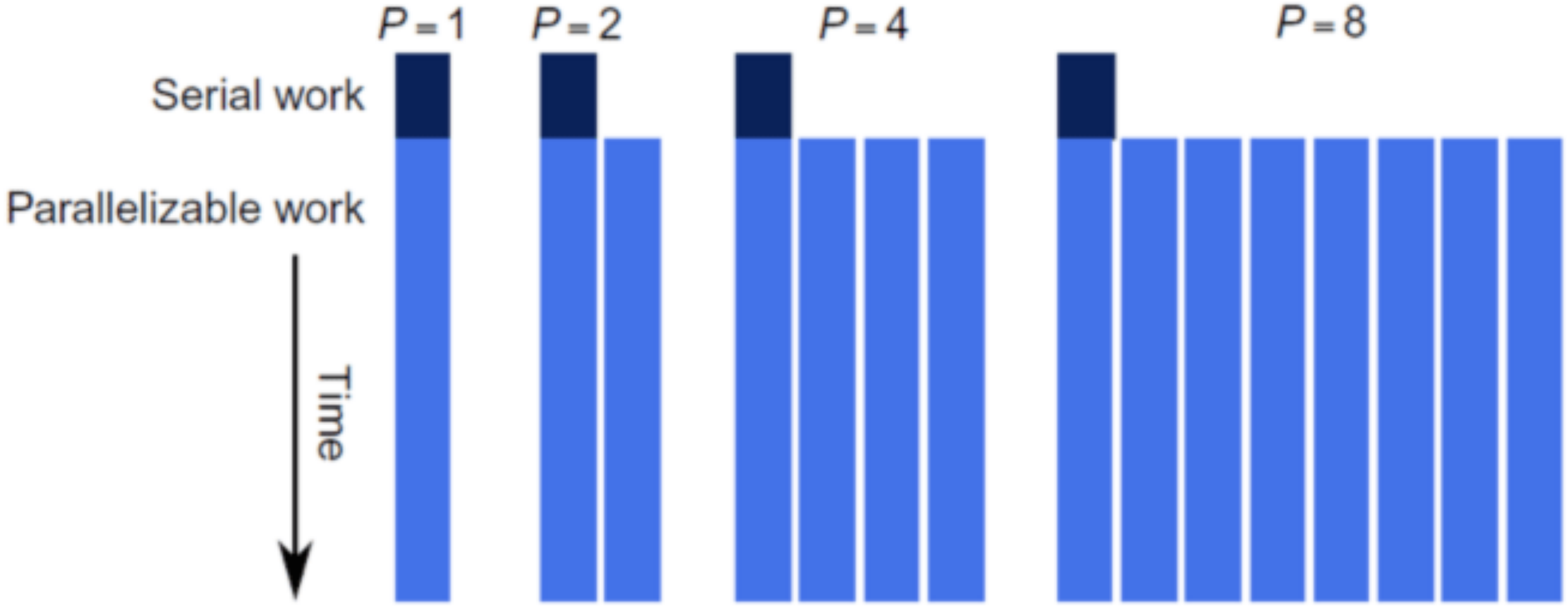
Gustafson's Law



Gustafson's Law



Gustafson's Law



Gustafson's Law

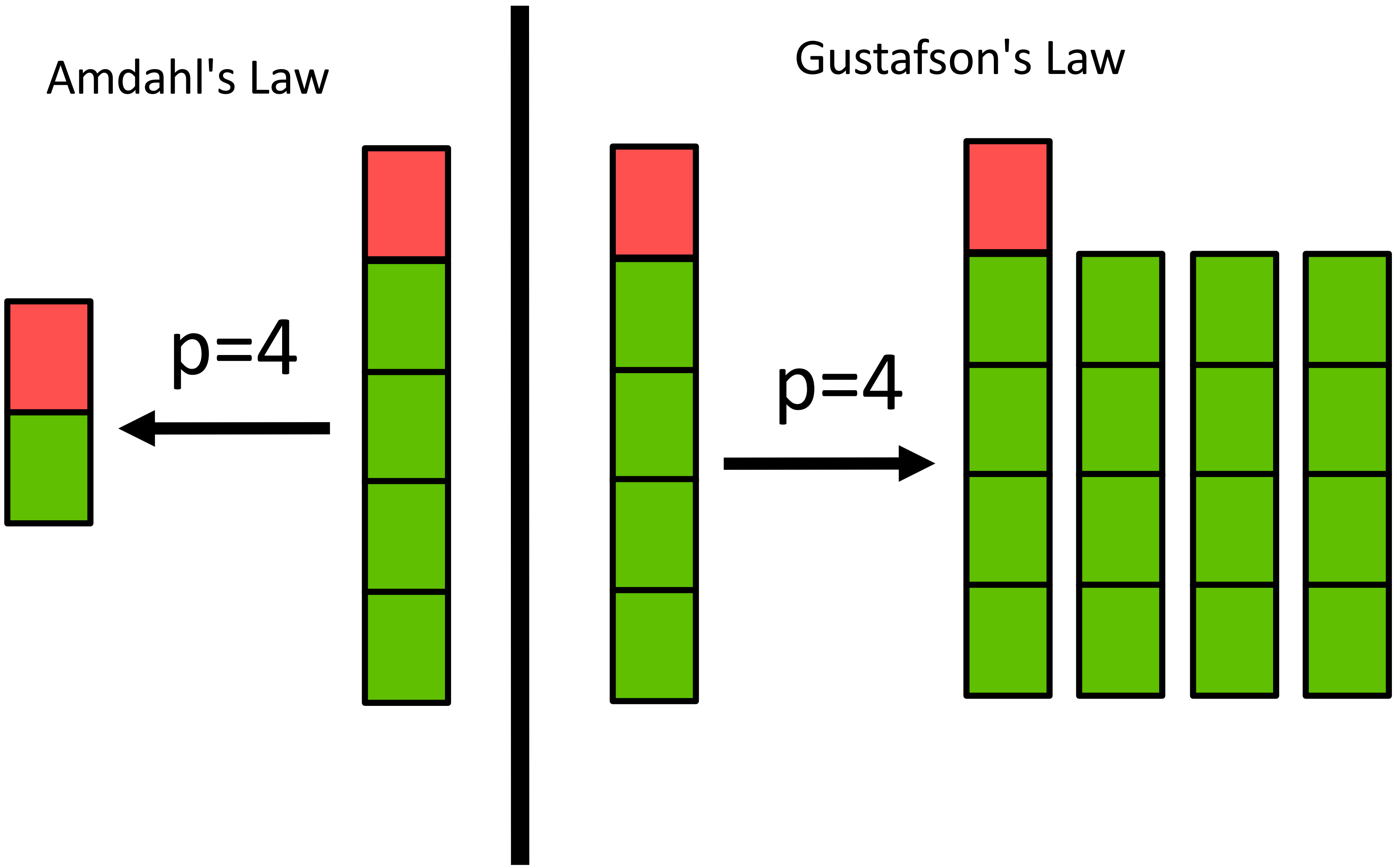
- f: sequential part (no speedup)

$$W = p(1 - f)T_{wall} + fT_{wall}$$

$$\begin{aligned} S_p &= f + p(1 - f) \\ &= p - f(p - 1) \end{aligned}$$

http://link.springer.com/referenceworkentry/10.1007%2F978-0-387-09766-4_78

Amdahl's vs Gustafson's Law



Summary

- Parallel speedup
- Amdahl's and Gustafson's law
- Parallelism: task/thread granularity