

Amdahl's Law

The necessity to parallelize

Balázs Pál

Eötvös Loránd University

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- Algorithms can easily exceed any reasonable amount of runtime.
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 - There are task that can be solved only sequentially (eg. reading from disk).
 - There are task which requires a lot of effort and work to parallelize.
- We expect - or at least hope - that parallelization shortens runtime significantly.



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- Sequential part (S)
 - Takes a lot of time in every case, because this part is not parallelizable.
- Parallel part (P)
 - Doing the same operations in parallel on a lot of batch of data.
 - Should be always a lot faster than S .



- Amdahl's law now can be formulated as the following:

$$Q_{\text{speedup}}(N) = \frac{1}{S + \frac{P}{N}} = \frac{1}{S + \frac{1-S}{N}}, \quad (2)$$

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- The behaviour of the Q speedup's value can be expressed as

$$\begin{cases} Q_{\text{speedup}} = \frac{1}{S} & \text{if } N \rightarrow \infty \\ Q_{\text{speedup}} < \frac{1}{S} & \text{else} \end{cases} \quad (3)$$



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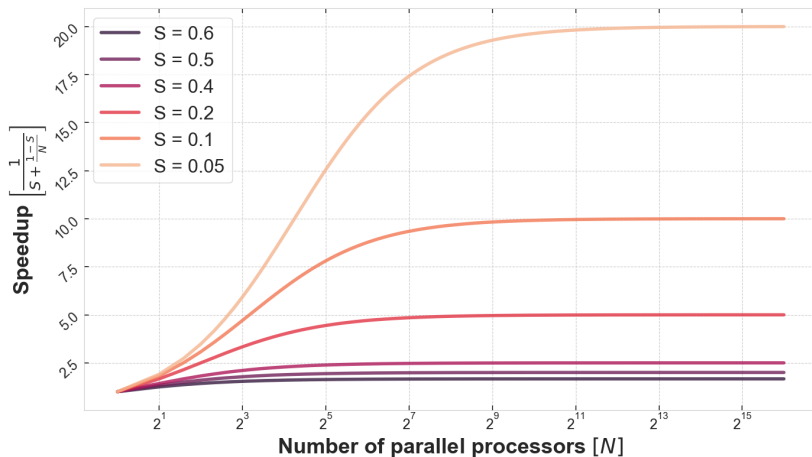


Figure 1: Visualization of the speedup with increasing number of parallel processors for different values of S . The figure shows that when the sequential part of the task is just the small portion of the whole algorithm, then the speedup is the highest. It can also be seen, that the limit for the speedup is $\lim_{N \rightarrow \infty} = \frac{1}{S}$