# Performance evaluation of parallel programs

Pacheco, Section 2.6

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Slides realized using material provided by Prof. Moreno Marzolla



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### Scalability

- How much faster can a given problem be solved with p workers instead of one?
- How much more work can be done with p workers instead of one?
- What impact for the communication requirements of the parallel application have on performance?
- What fraction of the resources is actually used productively for solving the problem?

### Speedup

- Let us define:
  - -p = Number of processors / cores
  - $T_{\text{serial}}$  = Execution time of the serial program
  - $T_{\text{parallel}}(p)$  = Execution time of the parallel program with p processors / cores

### Speedup

Speedup S(p)

$$S(p) = \frac{T_{\text{serial}}}{T_{\text{parallel}}(p)} \approx \frac{T_{\text{parallel}}(1)}{T_{\text{parallel}}(p)}$$

- In the ideal case, the parallel program requires 1/p the time of the sequential program
- S(p) = p is the ideal case of linear speedup
  - Realistically,  $S(p) \le p$
  - Is it possible to observe S(p) > p?



### Warning



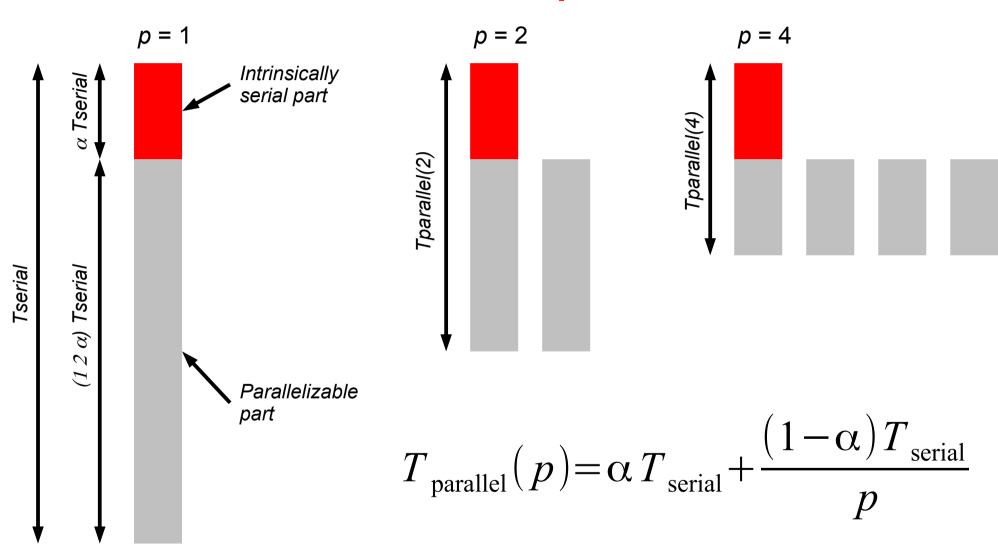
- Never use a serial program to compute  $T_{\text{serial}}$ 
  - If you do that, you might see a spurious superlinear speedup that is not there
- Always use the parallel program with p = 1 processors

### Non-parallelizable portions

- Suppose that a fraction α of the total execution time of the serial program can not be parallelized
  - E.g., due to:
    - Algorithmic limitations (data dependencies)
    - Bottlenecks (e.g., shared resources)
    - Startup overhead
    - Communication costs
- Suppose that the remaining fraction (1 α) can be fully parallelized
- Then, we have:

$$T_{\text{parallel}}(p) = \alpha T_{\text{serial}} + \frac{(1-\alpha)T_{\text{serial}}}{p}$$

### Example



### Example

- Suppose that a program has  $T_{\text{serial}} = 20$ s
- Assume that 10% of the time is spent in a serial portion of the program
- Therefore, the execution time of a parallel version with p processors is

$$T_{\text{parallel}}(p) = 0.1 T_{\text{serial}} + \frac{0.9 T_{\text{serial}}}{p} = 2 + \frac{18}{p}$$

### Example (cont.)

The speedup is

$$S(p) = \frac{T_{\text{serial}}}{0.1 \times T_{\text{serial}} + \frac{0.9 \times T_{\text{serial}}}{p}} = \frac{20}{2 + \frac{18}{p}}$$

 What is the maximum speedup that can be achieved when p → +∞?

### Amdahl's Law

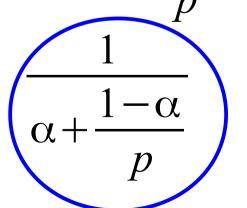
What is the maximum speedup?

$$S(p) = \frac{T_{\text{serial}}}{T_{\text{parallel}}(p)}$$

$$= \frac{T_{\text{serial}}}{\alpha T_{\text{serial}} + \frac{(1-\alpha)T_{\text{serial}}}{p}}$$



Gene Myron Amdahl (1922-2015)



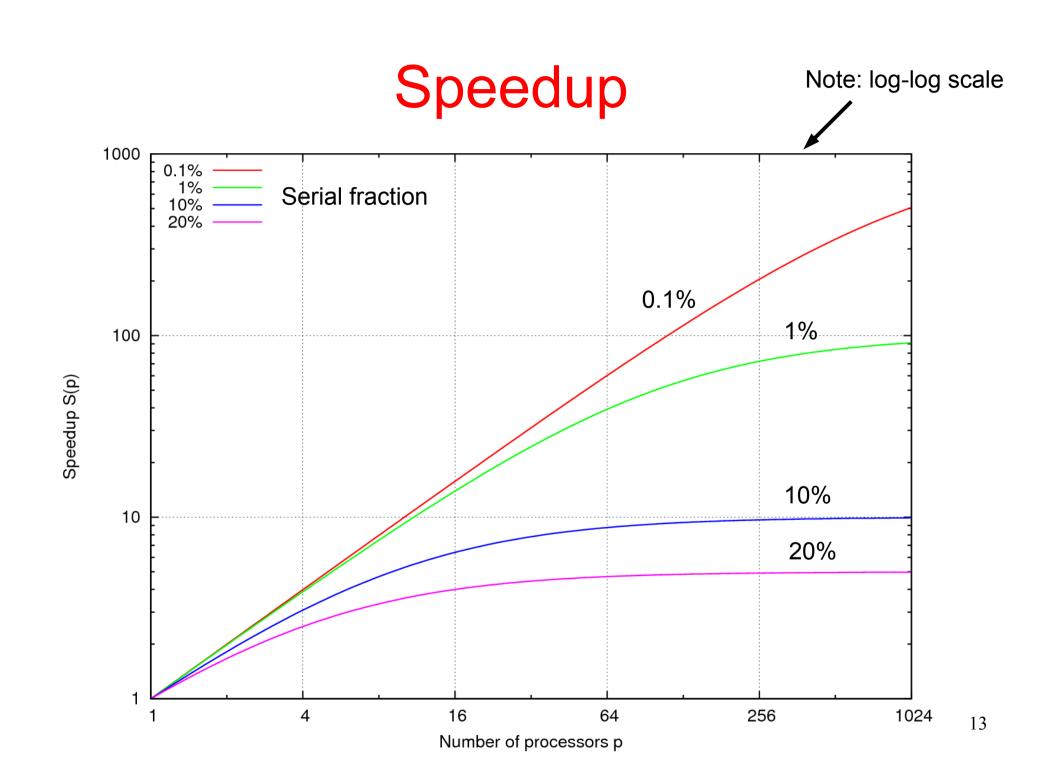
### Amdahl's Law

From

$$S(p) = \frac{1}{\alpha + \frac{(1-\alpha)}{p}}$$

we get an asymptotic speedup  $1/\alpha$  when p grows to infinity

If a fraction  $\alpha$  of the total execution time is spent on a serial portion of the program, then the maximum achievable speedup is  $1/\alpha$ 



### Scaling Efficiency

#### Objective:

- Evaluate the impact of Amdahl's law on your parallel program
- Quantify the effect on the execution time for each processor/core that is added
- Solution: measure Strong Scaling
  - Increase the number of processors p keeping the total problem size fixed
  - The total amount of work remains constant, while the amount of work for each processor decreases as p increases
  - How to quantify the impact of each added processor/core?
    - Divide the speedup for the number of processors/cores
  - Goal: understand how much the total execution time is reduced by adding more processors

### Strong Scaling Efficiency

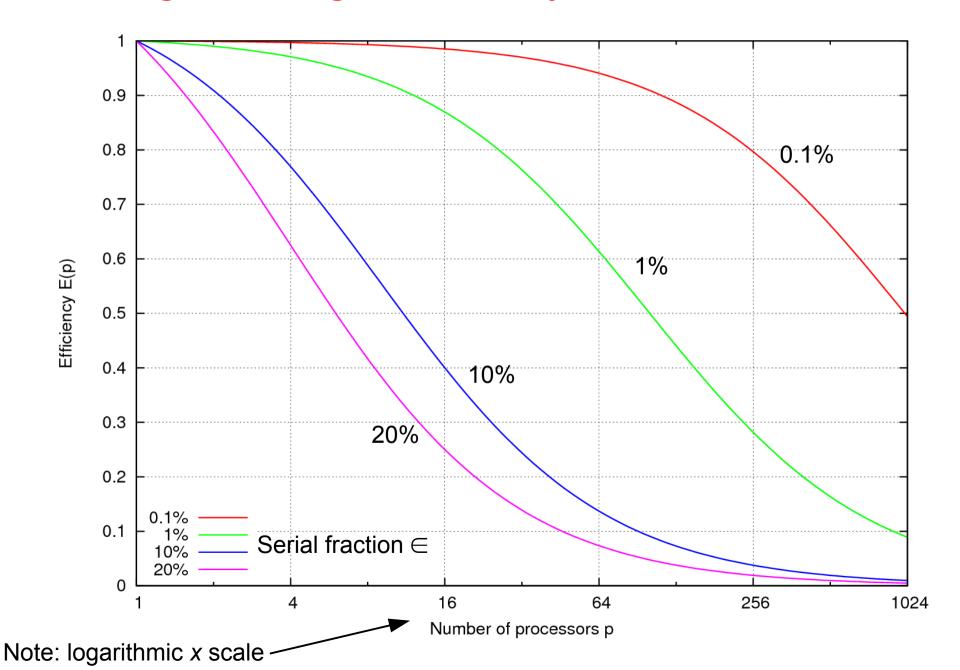
• E(p) = Strong Scaling Efficiency

$$E(p) = \frac{S(p)}{p} = \frac{T_{\text{parallel}}(1)}{p \times T_{\text{parallel}}(p)}$$

#### where

-  $T_{\text{parallel}}(p)$  = Execution time of the parallel program with p processors / cores

### Strong Scaling Efficiency and Amdahl's Law

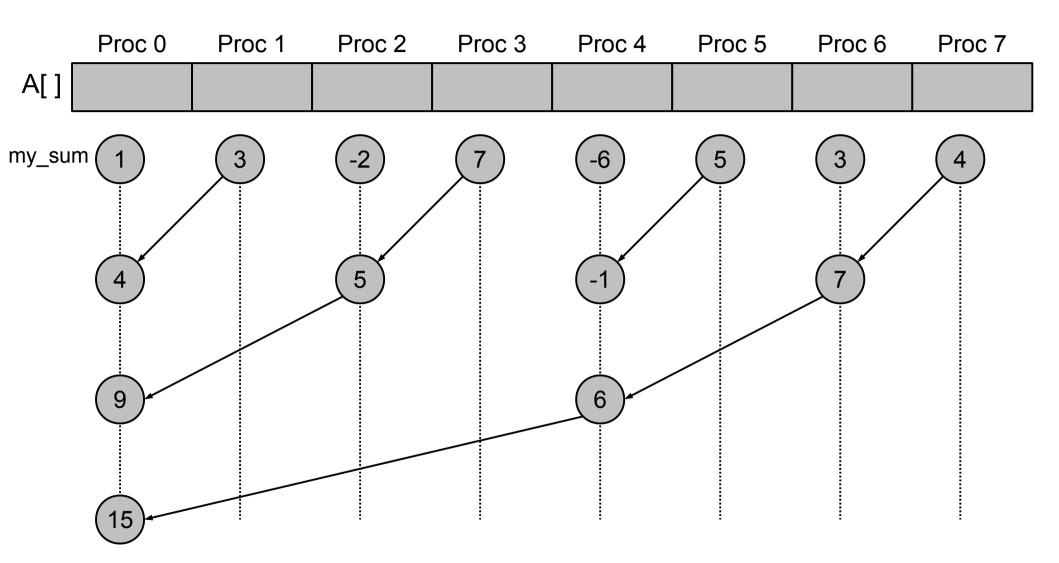


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## Negative result on strong scaling efficiency

- The efficiency always tends to zero because the speedup is limited by the constant 1/α
- But in many cases (remember the initial discussion about the need for more computational power) we want to use parallelism to do more computational work
  - If we consider increasing work, i.e., bigger input, the speedup could grow indefinitely
  - An example: vector sum reduction recalled in the next slide

### Vector sum reduction



• In principle, with n processors we sum n values in  $O(\log_2 n)$  time

### Speedup with increasing work

#### Observations:

- Summing *n* values requires *O*(*n*) work (*n* constant operations)
- To increase the work by a factor *p*, we consider *p* x *n* values
- Speedup( p)= $\frac{T_{seq}(p)}{T_{par}(p)}$ = $\frac{O(p\times n)}{O(\log(p\times n))}$  hence  $\lim_{p\to +\infty} Speedup(p)$ =+ $\infty$

#### This means:

- if we increase both work and number of processors / cores, the speedup can increase (in principle) unboundedly
- In these cases, according to Amdahl's terminology, we have that the serial fraction α decreases when the work increases

### Weak Scaling Efficiency

- An alternative measure that considers increasing problem size is Weak Scaling:
  - Increase the number of processors p keeping the perprocessor work fixed
  - The total amount of work grows as *p* increases
  - Goal: solve larger problems within the same amount of time
- W(p) = Weak Scaling Efficiency

$$W(p) = \frac{T_1}{T_p}$$

#### where

- $T_1$  = time required to complete 1 work unit with 1 processor
- $\frac{T_p}{p}$  = time required to complete p work units with p processors

### Example

#### See omp-matmul.c

- demo-strong-scaling.sh computes the times required for strong scaling
- demo-weak-scaling.sh computes the times required for weak scaling

#### Important note

- For a given n, the amount of "work" required to compute the product of two  $n \times n$  matrices is  $\sim n^3$
- To double the total work, do not double n!
  - The amount of work required to compute the product of two  $(2n \ Y2n)$  matrices is  $\sim 8n^3$ , eight times the  $n \times n$  case
- To double the work, we must use matrices of size  $(\sqrt[3]{2}n \times \sqrt[3]{2}n)$
- In general, with p processes we use matrices of size  $(\sqrt[3]{p}n \times \sqrt[3]{p}n)$

### Taking times

 To compute speedup and efficiencies one needs to take the program wall clock time, excluding the input/output time

```
#include <omp.h>
...
double start, finish;
/* read input data; this should not be measured */

start = omp_get_wtime();
/* actual code that we want to time */
finish = omp_get_wtime();

printf("Elapsed time = %e seconds\n", finish - start);

/* write output data; this should not be measured */
```