

Parallel & Distributed Computing: Lecture 5b

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Center

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Concepts and Terminology

- 1 Some General Parallel Terminology
- 2 Limits and Costs of Parallel Programming

Some General Parallel Terminology

Synchronization & Granularity

Synchronization The **coordination of parallel tasks in real time**, very often associated with communications.

Often implemented by **establishing** a **synchronization point** within an application where a **task may not proceed further** until another task(s) reaches the same or logically equivalent point.

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- **Coarse:** relatively large amounts of computational work are done between communication events
- **Fine:** relatively small amounts of computational work are done between communication events

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- Task termination time

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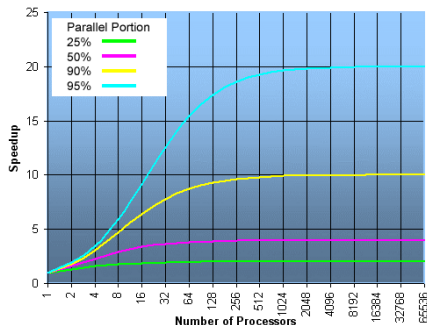
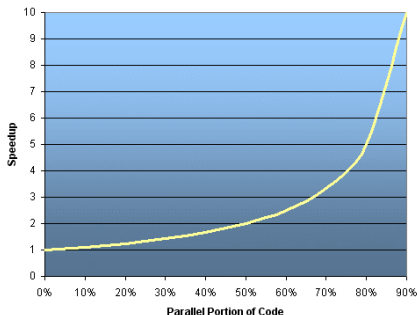
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- Characteristics of your specific application

Limits and Costs of Parallel Programming

Amdahl's Law 1/4

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$$\text{speedup} = \frac{1}{1 - P}$$

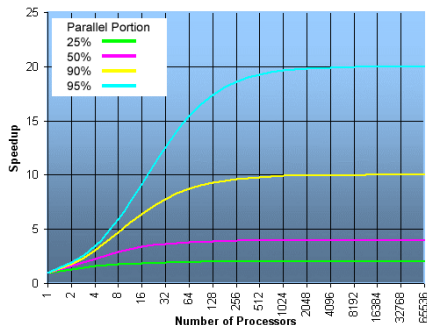
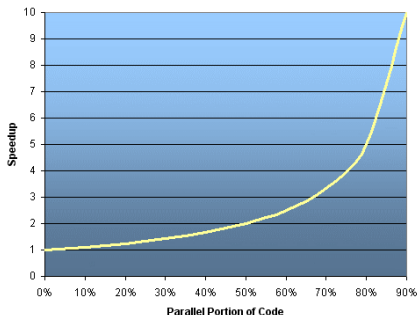


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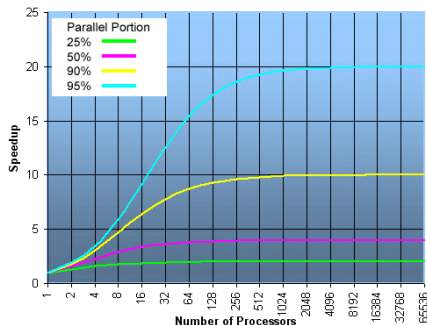
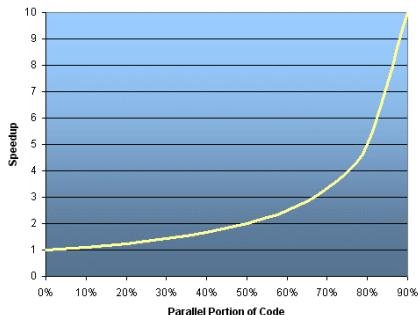


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- If all code is parallelized, $P = 1$ and the speedup = ∞ (in theory).
- If 50% of code can be parallelized, $\max(\text{speedup}) = 2$, meaning the code may run twice as fast.

Amdahl's Law 2/4

Introducing the number N of processors performing the parallel fraction of work, the relationship can be modeled by:

$$\text{speedup} = \frac{1}{\frac{P}{N} + S}$$

where P = parallel fraction, N = number of processors and S = serial fraction.

Amdahl's Law 3/4

It soon becomes obvious that **there are limits** to the **scalability of parallelism**

For example:

| N | speedup | | |
|---------|---------|---------|---------|
| | P = .50 | P = .90 | P = .99 |
| 10 | 1.82 | 5.26 | 9.17 |
| 100 | 1.98 | 9.17 | 50.25 |
| 1,000 | 1.99 | 9.91 | 90.99 |
| 10,000 | 1.99 | 9.91 | 99.02 |
| 100,000 | 1.99 | 9.99 | 99.90 |

Figure 1: **Speedup table**

Amdahl's Law 4/4

However, certain problems demonstrate **increased performance** by increasing the **problem size**. For example:

| | | |
|----------------------|------------|-----|
| 2D Grid Calculations | 85 seconds | 85% |
| Serial fraction | 15 seconds | 15% |

We can increase the problem size by **doubling the grid** dimensions and **halving the time step**. This results in four times the number of grid points and twice the number of time steps. The timings then look like:

| | | |
|----------------------|-------------|--------|
| 2D Grid Calculations | 680 seconds | 97.84% |
| Serial fraction | 15 seconds | 2.16% |

Problems that **increase the percentage** of parallel time with their size are **more scalable** than problems with a fixed percentage of **parallel time**.

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- The **costs of complexity** are measured in **programmer time** in virtually every aspect of the software development cycle:
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 - Coding
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 - Maintenance
- Adhering to “**good**” **software development practices** is **essential** when working with parallel applications - especially if somebody besides you will have to work with the software.

Portability

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- **Hardware architectures** are characteristically **highly variable** and can affect portability.

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- For **short running** parallel programs, there can actually be a **decrease in performance** compared to a similar serial implementation. The **overhead costs** associated with setting up the parallel environment, task creation, communications and task termination can comprise a **significant portion** of the **total execution time** for short runs.

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 - **Strong scaling:** The total problem size stays fixed as more processors are added.
 - **Weak scaling:** The problem size **per processor** stays fixed as more processors are added.
- The ability of a parallel program's **performance to scale** is a result of a number of interrelated factors. Simply **adding more processors** is **rarely the answer**.

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- Parallel **support libraries** and **subsystems software** can limit scalability independent of your application.