# An Introduction into Parallelization Part II - Design

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May 16, 2025





#### Outline

- Parallel Programming Models (cont.)
  - Recap: Computer Architectures
  - Distributed Parallelism with Message Passing
  - Hybrid Models
- 2 Designing Parallel Programs
  - Understand your problem and tools
  - Partitioning Domain vs functional decomposition
  - Data Dependence / Race conditions
  - Synchronization
  - Communication
  - Load balancing
  - I/O
  - Performance Analysis & Tuning
  - Conclusions / tl;dr



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# **Parallel Programming Models**



# Parallel Programming Models - Overview

# THREE LEVELS OF PARALLEL PROGRAMMING







MULTITHREADING

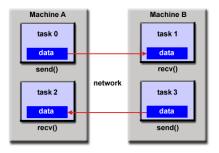


DISTRIBUTED PARALELLISM



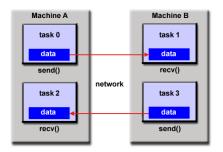
4 / 20

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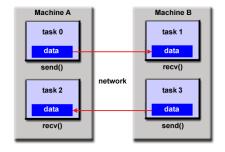


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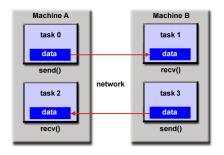


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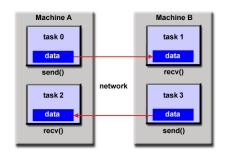


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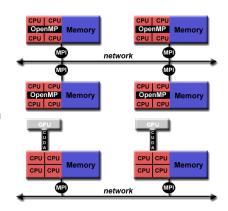
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- MPI is the "de facto" standard





# Hybrid Models

- Allows to make best use of locally shared memory or hardware, while still allowing for a good scalability across multiple nodes
- Comes with a significant increase in complexity/costs
- certain incompatibilities between libraries may exist (e.g. lack of thread-safety of MPI library)

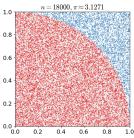




# **Designing Parallel Programs**

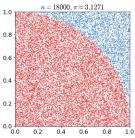


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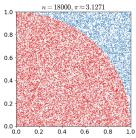


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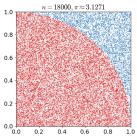


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- Identify inhibitors to parallelism: data-dependencies, I/O bottlenecks...
- Consider replacing your algorithms with equivalent ones bette suitedet for parallelism

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- pick optimal parallel programming model for your infrastructure
- make use of hardware optimization (e.g. vectorization, optimized libraries like MKL)
- identify hotspots in your program, i.e. routines where program spends lots of time in and check for improvement in parallelism ( $\rightarrow$ Amdahl's Law/Scaling)



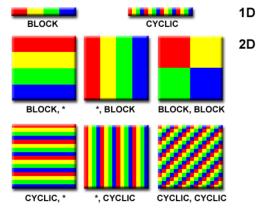
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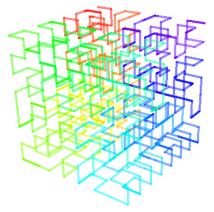


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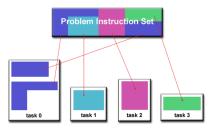
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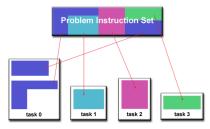
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• implemented e.g. in master/slave paradigm (see exercises)



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- This can also cause a so called race condition:

Thread 2		Integer value
		0
	<b>←</b>	0
		0
	<b>→</b>	1
read value	<b>←</b>	1
increase value		1
write back	<b>→</b>	2
	read value	← → read value ← increase value

Thread 1	Thread 2		Integer value
			0
read value		<b>←</b>	0
	read value	<b>←</b>	0
increase value			0
	increase value		0
write back		<b>→</b>	1
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- ... or to synchronize the calculations of processes (using barriers) for communication to exchange results or to redistribute the workload



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14 / 20

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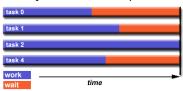
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  - ▶ Point-to-Point vs. collective communications



### Load balancing

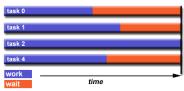
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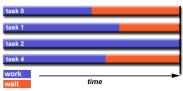


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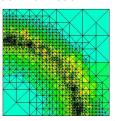


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- requires well-balanced workload distribution between processors
- difficult in heterogeneous, dynamic problem sets with incomplete information about the actual workload





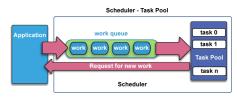
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- alternatively, use asynchronous approach with scheduler-task pool with smaller workload packages





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- more on this in the "HPC & (Big) Data" talk!



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  - applies to profiling, too!
- profilers do **NOT** tell you **HOW** to optimize your code, they metaly tell you **WHERE** to (potentially) do so for the best yield.

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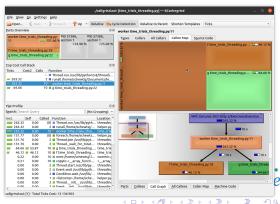
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- tools like profilers can help you to identify what to optimize, but you still need the knowledge on how to do this.

