

Networking and Scalability

Parallel Programming

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Dr. Georgiana Mania, Dr. Jannek Squar, Prof. Dr. Michael Kuhn
mania@dkrz.de, jannek.squar@uni-hamburg.de, michael.kuhn@ovgu.de

Parallel Computing and I/O
Institute for Intelligent Cooperating Systems
Faculty of Computer Science
Otto von Guericke University Magdeburg
<https://parcio.ovgu.de>

Networking and Scalability

Review

Introduction

Basics

Technologies

Scalability

Summary

- Which MPI thread mode is the default?
 1. `MPI_THREAD_SINGLE`
 2. `MPI_THREAD_FUNNELED`
 3. `MPI_THREAD_SERIALIZED`
 4. `MPI_THREAD_MULTIPLE`

- Which MPI thread mode is the default?
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 1. Blocking local
 2. Non-blocking local
 3. Blocking non-local
 4. Non-blocking non-local

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- Which function buffers data while sending?
 1. MPI_Send ()
 2. MPI_Bsend
 3. MPI_Isend
 4. MPI_Rsend

- Which function buffers data while sending?
 1. MPI_Send (✓)
 2. MPI_Bsend ✓
 3. MPI_Isend
 4. MPI_Rsend

- What is the difference between MPI_Reduce and MPI_Allreduce?
 1. MPI_Reduce performs a local operation, MPI_Allreduce across all ranks
 2. MPI_Reduce collects the value at the root rank, MPI_Allreduce at every rank
 3. MPI_Allreduce performs a barrier before, MPI_Reduce does not
 4. MPI_Allreduce performs a barrier afterwards, MPI_Reduce does not

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- Shared memory systems have limited scalability
 - Machines usually have two to four processors with a few dozen cores
 - OpenMP is a convenient and high-level programming concept
- Complex problems require more resources than available on a single node
 - Simulations require more computational power and main memory
 - Multiple nodes are connected via a so-called interconnect
- Distributed memory can be scaled almost arbitrarily
 - These typically consist of a cluster of shared memory systems
 - The largest machines have up to 10,000,000 cores in several thousand nodes

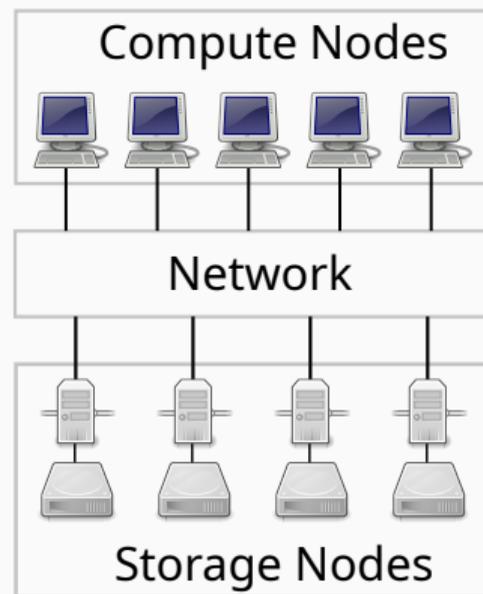
- Network connections are required to connect multiple nodes
 - Compute nodes have to communicate with each other
 - Storage nodes offer services via the network
- Necessary for inter-process communication across nodes
 - Shared memory objects enable communication on one node
 - Message passing is a programming concept for distributed memory
- Network can be designed using a variety of topologies
 - Bus, ring, star, fully connected mesh, fat tree etc.

- Processors require data fast
 - 3 GHz equals three operations per nanosecond
 - Even accessing the main memory is too slow
 - Cache levels hide main memory latency
- Network and I/O extremely slow in comparison
 - Waiting for an HDD ruins performance
 - SSDs have alleviated the problem a bit
 - Network adds additional latency

Level	Latency
L1 cache	≈ 1 ns
L2 cache	≈ 5 ns
L3 cache	≈ 10 ns
RAM	≈ 100 ns
InfiniBand	≈ 500 ns
Ethernet	≈ 100,000 ns
SSD	≈ 100,000 ns
HDD	≈ 10,000,000 ns

[Bonér, 2012] [Huang et al., 2014]

- Computation is only one part of parallel applications
 - Store data in main memory and persist it to storage
 - Main memory and storage per node is also limited
- Storage nodes are usually separate
 - Exclude influence on each other
 - Nodes can be tuned for their respective workloads
- Data has to be transferred for each I/O operation
 - I/O typically also includes network latency
 - Node-local buffers can be used as a workaround



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- Several components are necessary to build a network
 - Network interface cards (NIC)
 - Each node is equipped with one or more of them
 - Network cables
 - Supercomputers need hundreds to thousands of kilometers of cables
 - Fiber cables offer high frequencies and less loss than copper cables
 - Network switches
 - Multiple switches can be required depending on the network topology
- Network is often split into multiple sub-networks
 - Separate communication, storage and management networks

- Have to consider both the hardware and software perspective
- Network technology should be adaptable to different environments
 - Allow using different network topologies depending on requirements
- Different network technologies typically have different interfaces
 - For convenience reasons, a high level of abstraction is preferred
 - High performance might require breaking the high level of abstraction
- Data should be transferred as efficiently as possible
 - High numbers of system calls can have a negative performance impact
 - Some network technologies use kernel bypass to improve performance

- Performance characteristics are especially important in HPC
 - Network should introduce as little additional overhead as possible
- Bandwidth (in GBit/s or GB/s)
 - Actual throughput might be less due to protocol overhead etc.
- Latency (in ns)
 - Highly dependent on software overheads
 - Depending on distance, physics also becomes important (≈ 1 ms per 100 km)
- Robustness and error rate
 - Network should handle faults in single cables or switches
 - Other factors might cause errors that should be detected and corrected
- TCP/IP support
 - TCP usage is almost ubiquitous and some applications support nothing else

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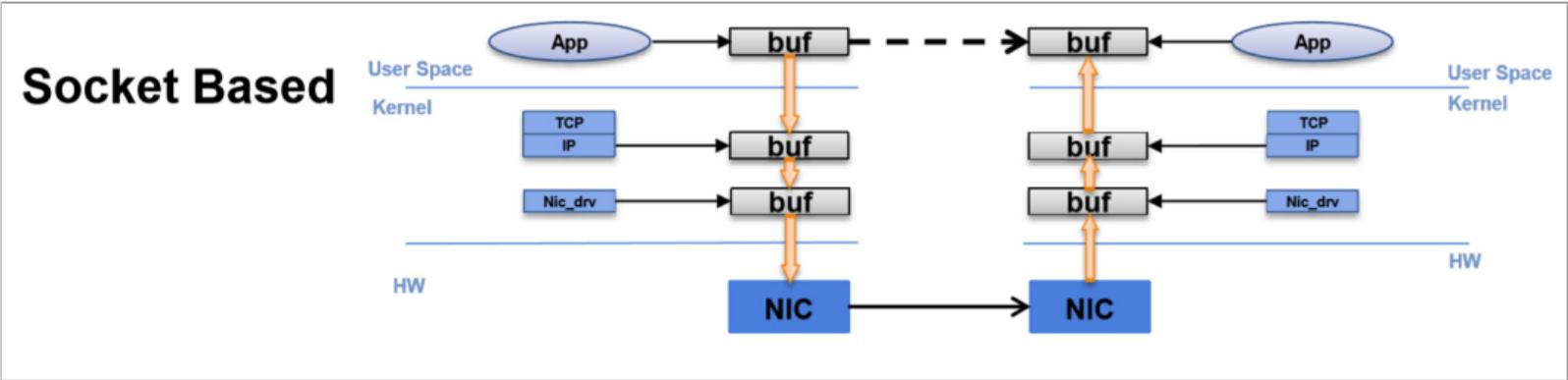
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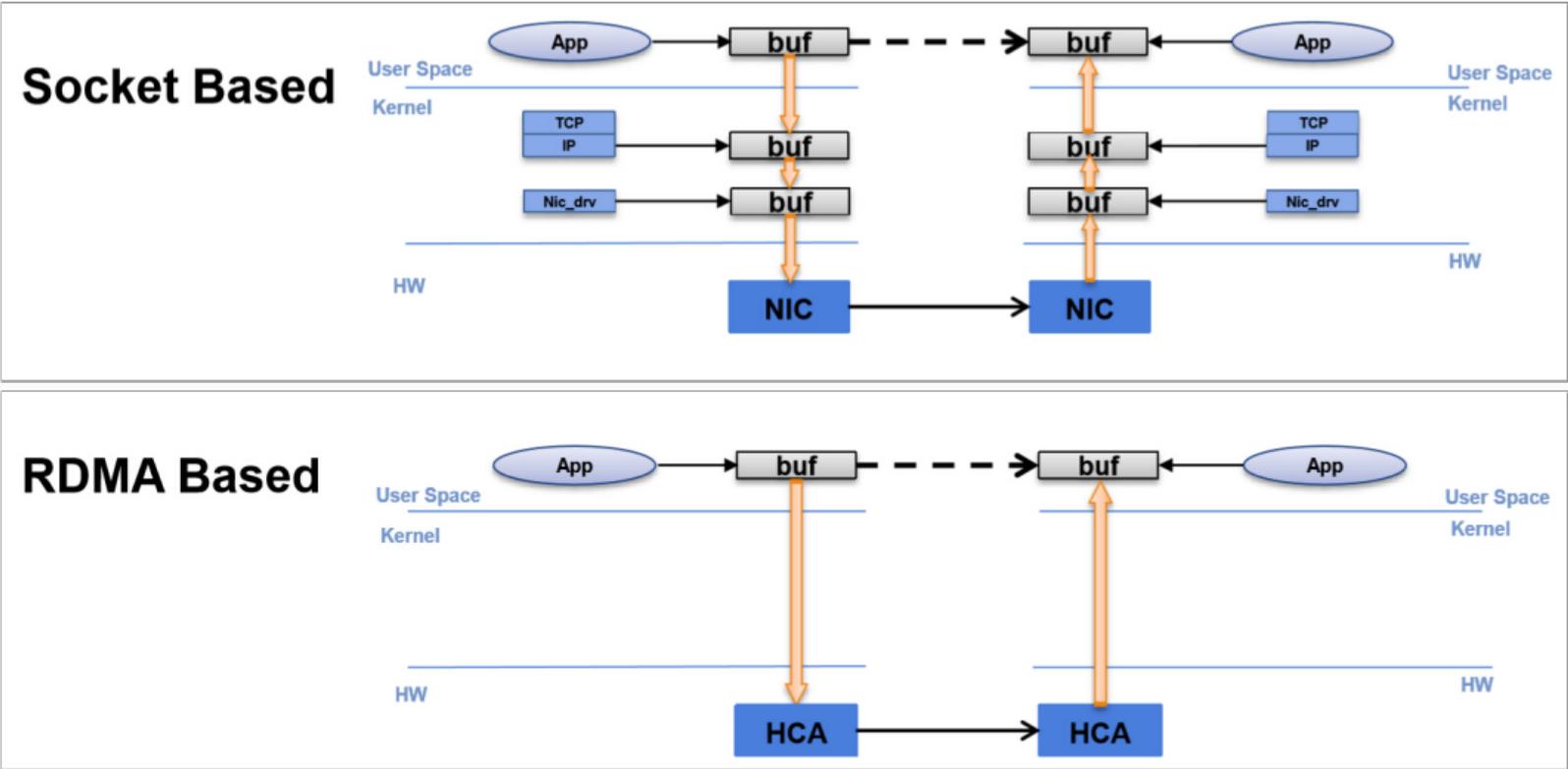
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- Different terminology depending on network technology
 - Ethernet uses a network interface card (NIC)
 - InfiniBand uses a host channel adapter (HCA)



[Chenfan, 2016]



[Chenfan, 2016]

- Remote direct memory access (RDMA)
 - Target's memory can be accessed directly without interruption
 - Memory might have to be registered and/or locked
- Zero copy
 - Avoid copies between user space and kernel space
 - Potential copies within the kernel (kernel buffer and driver buffer)
 - Additional copies between kernel space and device
- Copying is expensive from performance and energy perspectives
 - Copying data once reduces maximum throughput by a factor of two etc.

- Network stacks have been designed for different requirements
 - High latencies, low throughputs and potentially high error rates
 - TCP/IP includes support for retransmissions etc.
- Packets are typically small
 - Ethernet normally uses 1,500 bytes frames, TCP up to 64 KiB
 - Worst case: One interrupt per packet
- Operating systems implement their own network stacks
 - Operations have to be performed in software
 - Software overheads can be problematic for high-speed interconnects

- Interrupts can quickly accumulate for high packet rates
 - Interrupts prevent applications from performing computations
- Polling requires processor time to check for new packets
 - Can be more efficient if many packets can be retrieved at once
- Parts of network protocols can be provided in hardware
 - TCP Offload Engine is widely used to improve TCP performance
- DMA allows data to be copied without involving processor
 - Otherwise, processor would have to copy data actively

- Traditionally, talking to the network card requires the kernel
 - Kernel manages and talks to the NIC via a driver
 - Applications talk to kernel via system calls
- Context switches and interrupts cause high overhead
 - Kernel bypass allows applications to talk to the NIC directly
- Different approaches exist already [Majkowski, 2015]
 - Many require special hardware support or dedicated NICs
 - For instance, specialized network API that manages queues on NIC

- What are potential downsides of bypassing the kernel?
 1. Incompatibilities with the operating system
 2. Security cannot be enforced
 3. Missing support for TCP/IP

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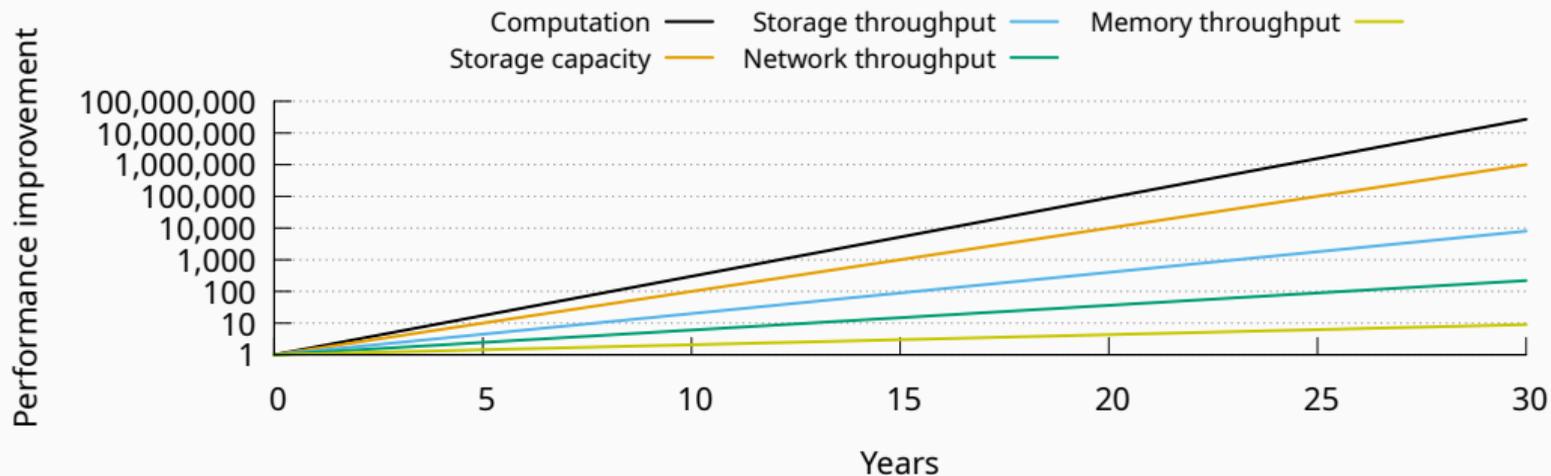
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- Hardware improves exponentially, but at different rates
 - Storage capacity and throughput are lagging behind computation
- Network and memory throughput are even further behind
 - Transferring data has become a very costly operation

- Network bandwidth has increased steadily over the years
- Two main competitors in HPC
 1. Ethernet
 2. InfiniBand
- InfiniBand supports multiple links
 - x1 is base performance
 - x4, x8 and x12 are faster

Technology	Bandwidth	Year
Ethernet	10 Mbit/s	1980
Fast Ethernet	100 Mbit/s	1995
Gigabit Ethernet	1 Gbit/s	1998
InfiniBand SDR x12	24 Gbit/s	2001
10 Gigabit Ethernet	10 Gbit/s	2002
InfiniBand QDR x12	96 Gbit/s	2007
100 Gigabit Ethernet	100 Gbit/s	2010
InfiniBand EDR x12	300 Gbit/s	2014
Omni-Path	100 Gbit/s	2015
400 Gigabit Ethernet	400 Gbit/s	2017
InfiniBand HDR x12	600 Gbit/s	2017
InfiniBand NDR x12	1,200 Gbit/s	2022
800 Gigabit Ethernet	800 Gbit/s	2024
InfiniBand XDR x12	2,400 Gbit/s	2024

[Wikipedia, 2024]

- InfiniBand is a networking standard
 - Promoted by the InfiniBand Trade Association
 - Mellanox is the major vendor for InfiniBand (now part of Nvidia)
- Mostly used in HPC due to high throughput and low latency
 - Throughputs up to 1,200 GBit/s
 - Latencies of less than 500 ns
- InfiniBand provides support for RDMA
 - Used by MPI's own RDMA support

- No standard API
 - Standard only has a list of verbs such as `ibv_open_device`
 - De-facto standard software stack by OpenFabrics Alliance
 - `libibverbs` for Linux, kernel support since 2005
- Packets of up to 4 KB for messages
 - RDMA read or write
 - Send or receive
 - Transaction operation
 - Multicast operation
 - Atomic operation

- How much throughput can we typically expect from Gigabit Ethernet?
 1. 10 MB/s
 2. 12 MB/s
 3. 100 MB/s
 4. 120 MB/s
 5. 1 GB/s
 6. 1.2 GB/s

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- Reminder: Scalability is ambiguous and can apply to different components
 - We have taken a look at the scalability of hardware architectures before
- How big we can scale something while keeping the benefits
 - How easy it is to increasing a network's size
 - How well invested money correlates with improved performance
 - How well an application can run on more cores/nodes
- We will now take a look at the scalability of parallel applications

- When writing parallel applications, we must consider scalability
 - Scalability describes how an application behaves with increasing parallelism
- HPC systems are usually very expensive and should be used accordingly
 - Procurement costs can reach up to € 250,000,000
- To determine scalability, we have to analyze performance
 - HPC systems are complex, performance yield is often not optimal
 - Many different components interact with each other
 - Processors, caches, main memory, network, storage system etc.

- In addition to procurement costs, operating costs are also quite high
 - 2. Frontier (USA): 1.35 EFLOPS at 24.6 MW \approx € 64,650,000/a (in Germany)
 - 9. LUMI (Finland): 380 PFLOPS at 7.1 MW \approx € 18,660,000/a (in Germany)
 - 163. Levante (Germany): 10 PFLOPS at 2 MW \approx € 5,250,000/a (at € 0.3 per kWh)
- Communication and I/O are often responsible for performance problems
 - High latency, which causes excessive waiting times for processors
 - Communication and I/O typically happen synchronously

- The performance improvement we get is called speedup
 - In the best case, the speedup is equal to the number of tasks
 - In reality, the speedup is usually lower due to overhead (communication, I/O etc.)
- Speedup can sometimes be higher than the number of tasks
 - This is called a superlinear speedup and usually points at a problem
 - For example, each task's data suddenly fits into the cache
 - This means that the measured problem became too small
 - Larger problems will not fit and therefore have a lower speedup

- Speedup: $S(n) = \frac{T(1)}{T(n)}$
 - $T(1)$: Runtime of one task
 - $T(n)$: Runtime of n tasks

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- Requirement: Choose fastest algorithm
 - $T(1)$ is not necessarily the parallel version executed with one task
 - Sometimes a serial algorithm might be the fastest choice

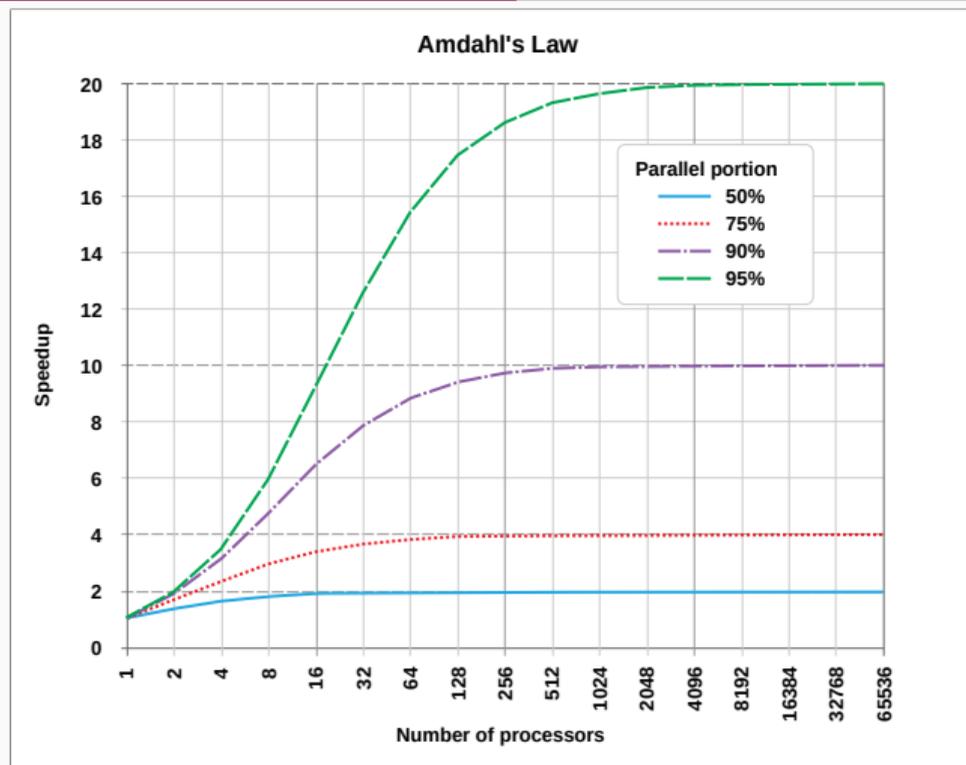
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- Efficiency: $E(n) = \frac{S(n)}{n}$
 - Normalizes the speedup to the $[0, 1]$ range

- Amdahl's law describes an upper limit for the speedup
 - Every application contains a serial portion that limits the speedup
- f is the serial portion ($\in [0, 1]$)

$$S(n) = \frac{1}{f + \frac{1-f}{n}} \Rightarrow S_{max} = \frac{1}{f}$$

- Even seemingly small serial portions have a large impact
 - $f = 0.01 \Rightarrow S_{max} = 100$
 - Try to keep serial portion as small as possible
- Problem: Only applies if problem size is fixed
 - It usually makes sense to increase the problem size if more nodes are available

- Examples
 - 5 % serial portion
 - $S_{max} = 20$
 - 50 % serial portion
 - $S_{max} = 2$
- Parallelization might sometimes not be worth it
 - Weigh up required effort against potential speedup



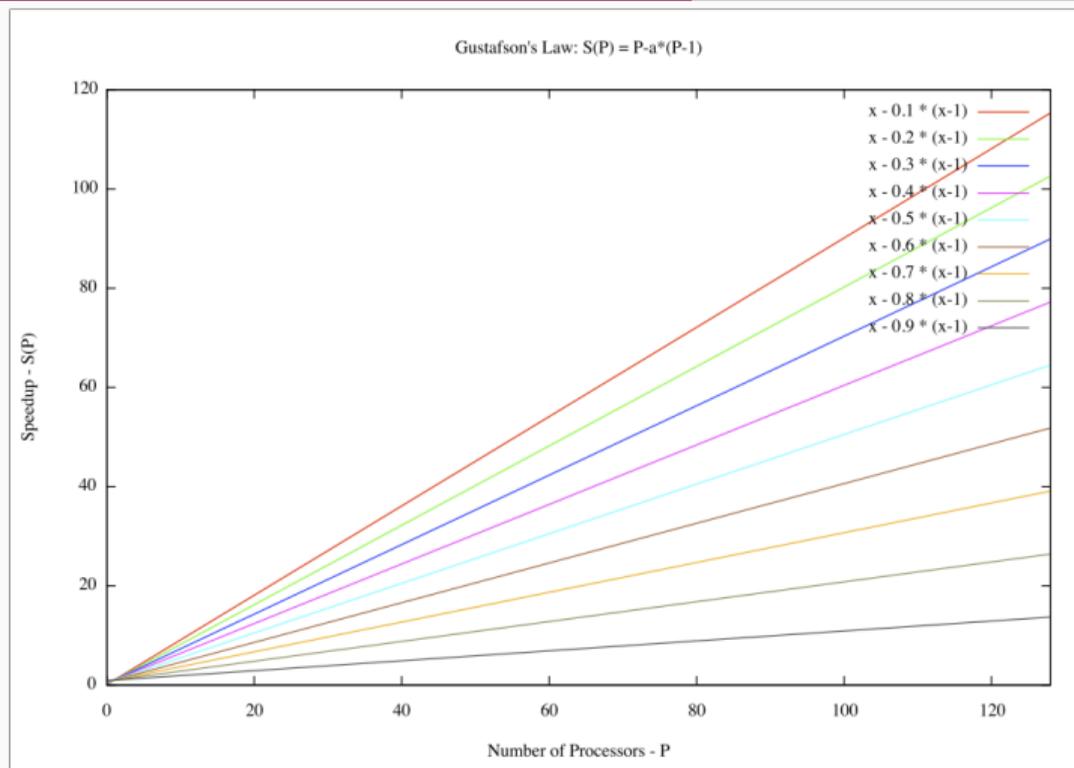
[Daniels220, 2008]

- Gustafson's law also describes an upper limit for the speedup
 - In contrast to Amdahl's law, problem size can be increased
 - However, time has to be fixed (problem size has to be chosen appropriately)
 - Every application contains a serial portion
- f is the serial portion ($\in [0, 1]$)

$$S(n) = n + f(1 - n) = n + f - fn = n - fn + f = n - f(n - 1)$$

- Also does not apply to all kinds of applications
 - Problem sizes cannot always be scaled up arbitrarily

- Examples
 - 5 % serial portion
 - $S(120) = 114$
 - 50 % serial portion
 - $S(120) = 60$
- Much better than with Amdahl's law
 - Increasing problem size compensates overhead



[Peahihawaii, 2011]

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- Strong scaling
 - Increase task count with constant problem size (related to Amdahl's law)
- Example: Matrix calculation
 - Matrix contains $1,000 \times 1,000$ elements
 - Calculation for one element requires elements from neighbors

- Parallelization with 5 tasks
 - Each task has a sub-matrix of $200 \times 1,000$ elements
 - Each task has to communicate $2 \times 1,000$ elements with others
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- Parallelization with 10 tasks
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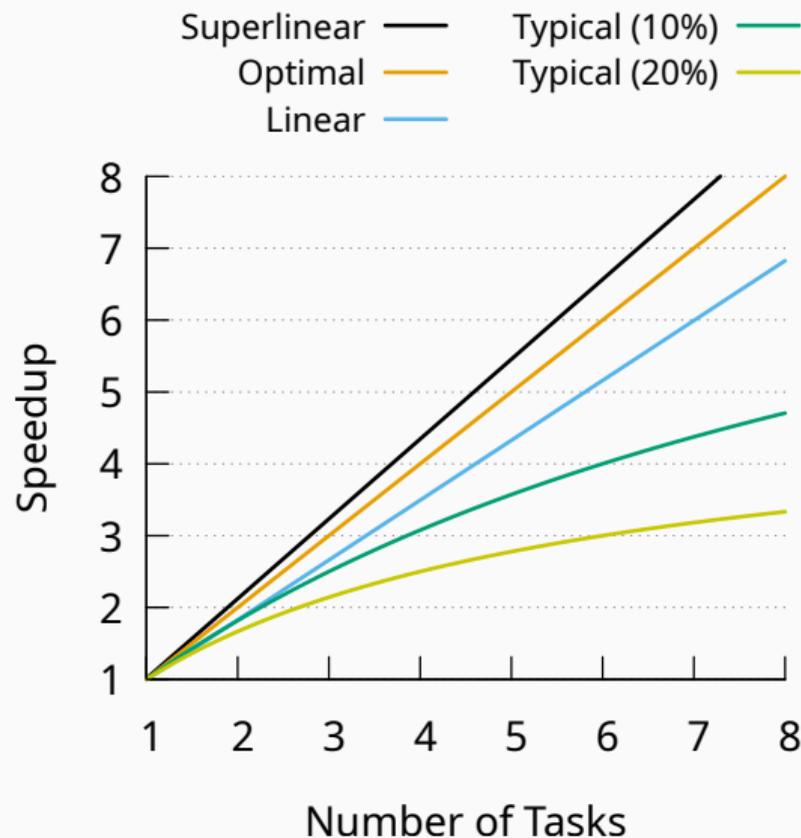
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- Parallelization with 100 tasks
 - Each task has a sub-matrix of $10 \times 1,000$ elements
 - Each task has to communicate $2 \times 1,000$ elements with others
 - Communication-to-computation ratio is 1:5

- Parallelization with 10 tasks and doubled matrix size
 - Each task has a sub-matrix of $141 \times 1,414$ elements
 - Each task has to communicate $2 \times 1,414$ elements with others
 - Communication-to-computation ratio is 1:70

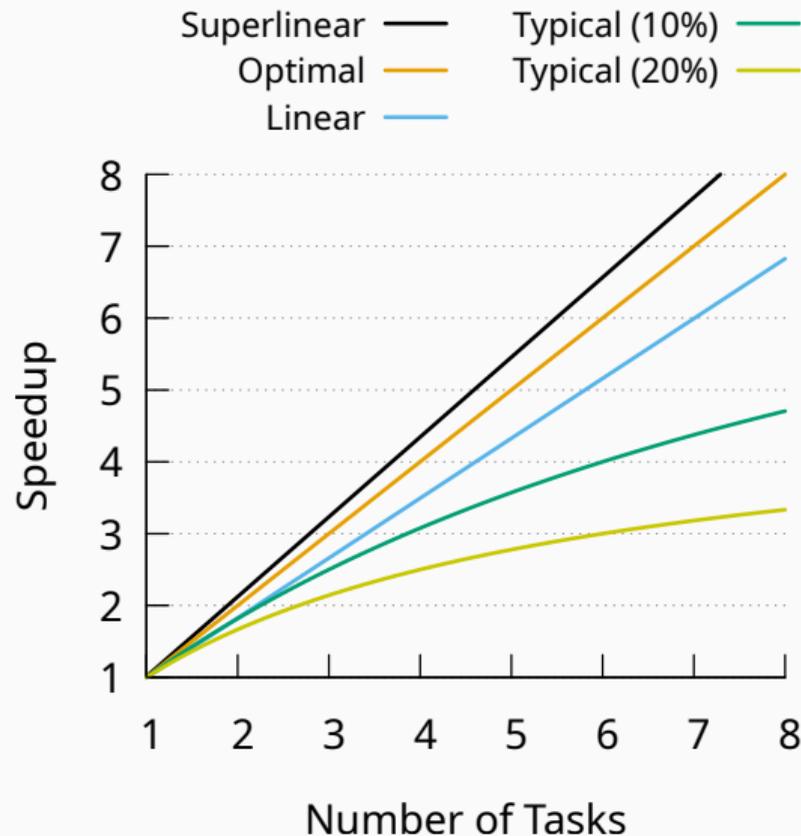
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 - Communication-to-computation ratio is 1:70
- Parallelization with 10 tasks and tenfold matrix size
 - Each task has a sub-matrix of $316 \times 3,162$ elements
 - Each task has to communicate $2 \times 3,162$ elements with others
 - Communication-to-computation ratio is 1:158

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 - Each task has to communicate $2 \times 1,414$ elements with others
 - Communication-to-computation ratio is 1:70
- Parallelization with 10 tasks and tenfold matrix size
 - Each task has a sub-matrix of $316 \times 3,162$ elements
 - Each task has to communicate $2 \times 3,162$ elements with others
 - Communication-to-computation ratio is 1:158
- Parallelization with 100 tasks and hundredfold matrix size
 - Each task has a sub-matrix of $100 \times 10,000$ elements
 - Each task has to communicate $2 \times 10,000$ elements with others
 - Communication-to-computation ratio is 1:50

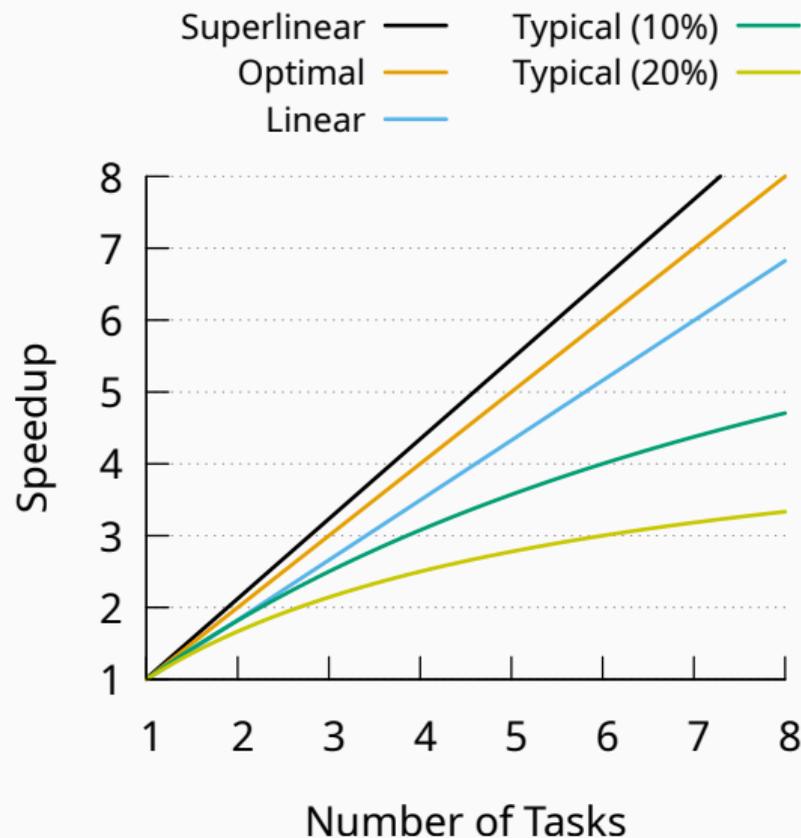
- Speedup graphs visualize performance



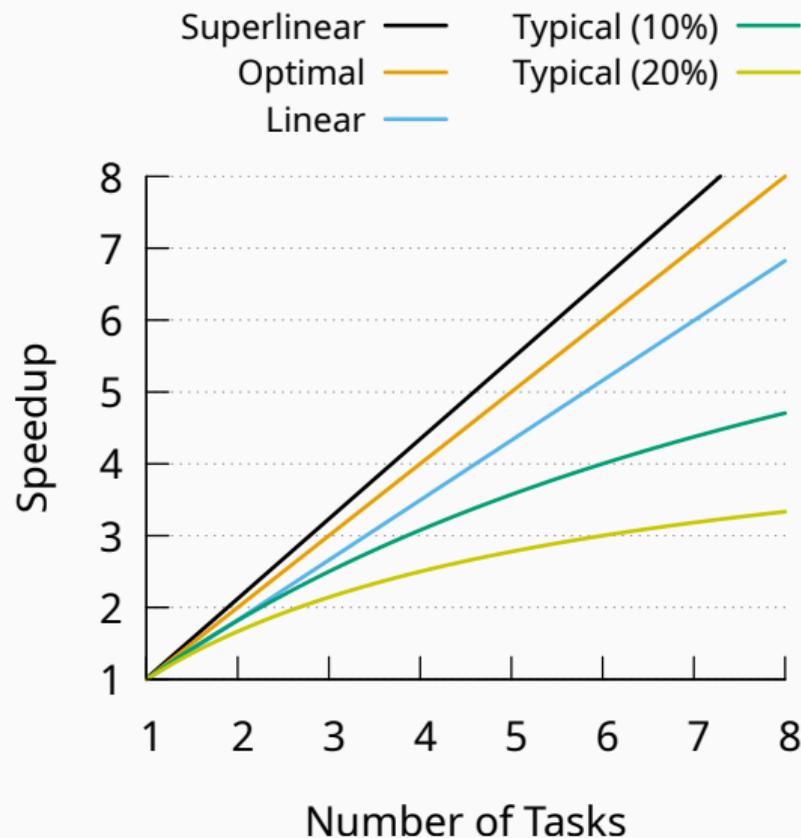
- Speedup graphs visualize performance
- Optimal speedup
 - Perfect scaling, no overhead



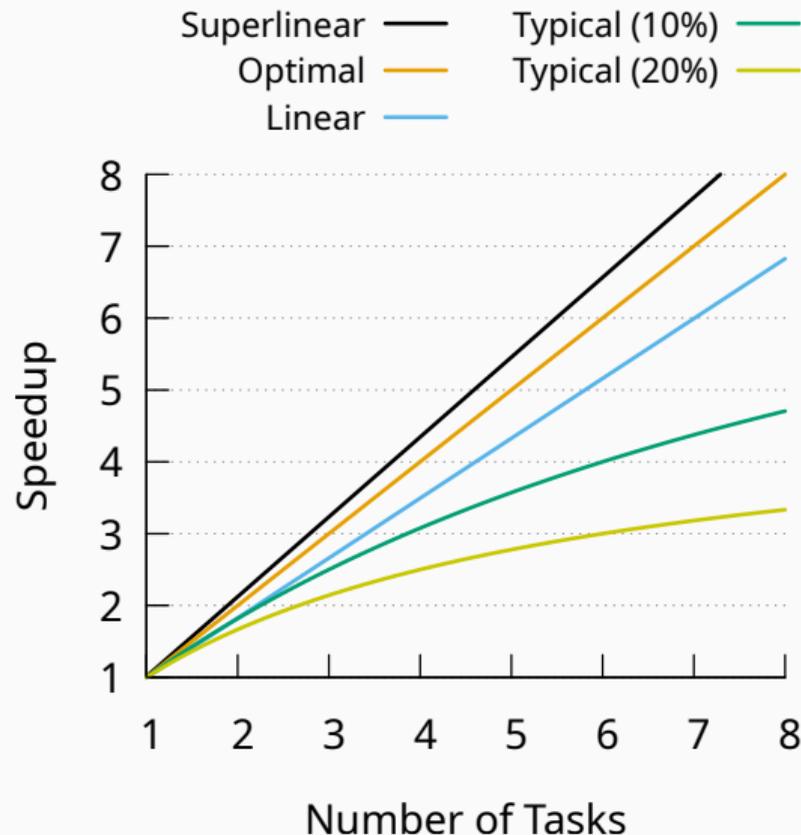
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- Speedup graphs visualize performance
- Optimal speedup
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- Typical speedup
 - Overhead keeps growing
 - With 10 or 20 % serial portion according to Amdahl's law
- Superlinear speedup
 - Negative overhead?



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 - We have n search algorithms with runtimes t_i
 - Want to find the fastest one

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- Serial version
 1. Set $t_{min} = \infty$
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 - 2.2 Otherwise, set $t_{min} = t_i$

- Example: Comparing search algorithms
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- Serial version
 1. Set $t_{min} = \infty$
 2. Run each algorithm i
 - 2.1 If it runs longer than t_{min} , terminate it
 - 2.2 Otherwise, set $t_{min} = t_i$
- The serial version has a runtime of $t_{serial} \geq t_{min} \times n$
 - $t_{serial} > t_{min} \times n$ if we do not run the fastest algorithm first

- Parallel version
 1. Run each algorithm i on its own core
 - 1.1 As soon as the first one finishes, set $t_{min} = t_i$ and terminate all other algorithms

- Parallel version
 1. Run each algorithm i on its own core
 - 1.1 As soon as the first one finishes, set $t_{min} = t_i$ and terminate all other algorithms
- The parallel version has a runtime of $t_{parallel} = t_{min}$

$$S = \frac{t_{serial}}{t_{parallel}} \Rightarrow S \geq \frac{t_{min} \times n}{t_{min}} \Rightarrow S \geq n$$

- What mistake did we make to achieve a superlinear speedup?
 1. We did not make a mistake
 2. We did not choose the fastest serial algorithm
 3. We cannot run each algorithm on its own core

- What mistake did we make to achieve a superlinear speedup?
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 1. Run each algorithm i for a time slice t
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- Improved serial version
 1. Run each algorithm i for a time slice t
 - 1.1 As soon as the first one finishes, set $t_{min} = t_i$ and terminate all other algorithms
- The improved version has a runtime of $t_{serial} \approx t_{min} \times n$
 - Overhead depends on length of the time slice
 - This gets rid of the superlinear speedup

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- Networking is necessary to build distributed memory systems
 - Shared memory systems have limited scalability
- Network technologies have different performance characteristics
 - The two major competitors are Ethernet and InfiniBand
- High-performance networking requires optimizations
 - RDMA, zero copy, offloading and kernel bypass help reduce overhead
- Scalability can be measured using speedup and efficiency
 - There are limits to scalability, demonstrated by Amdahl and Gustafson's laws

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