rCUDA: towards energy-efficiency in GPU computing by leveraging low-power processors and InfiniBand interconnects

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Joint research effort

Outline

- Current GPU computing facilities
- How GPU virtualization adds value to your cluster
- The rCUDA framework: basics and performance
- Integrating rCUDA with SLURM
- rCUDA and low-power processors

Outline

- **Current GPU computing facilities**
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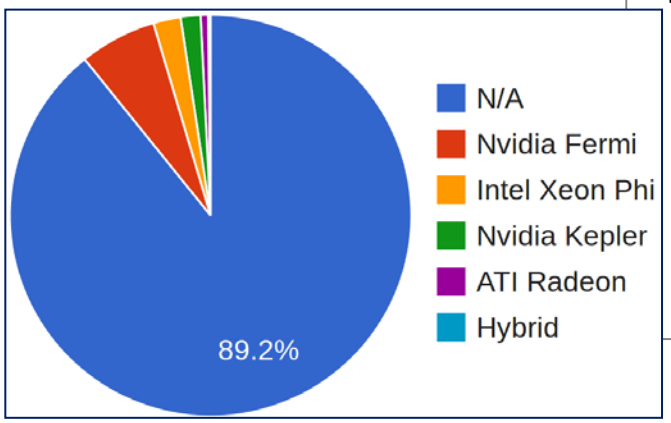
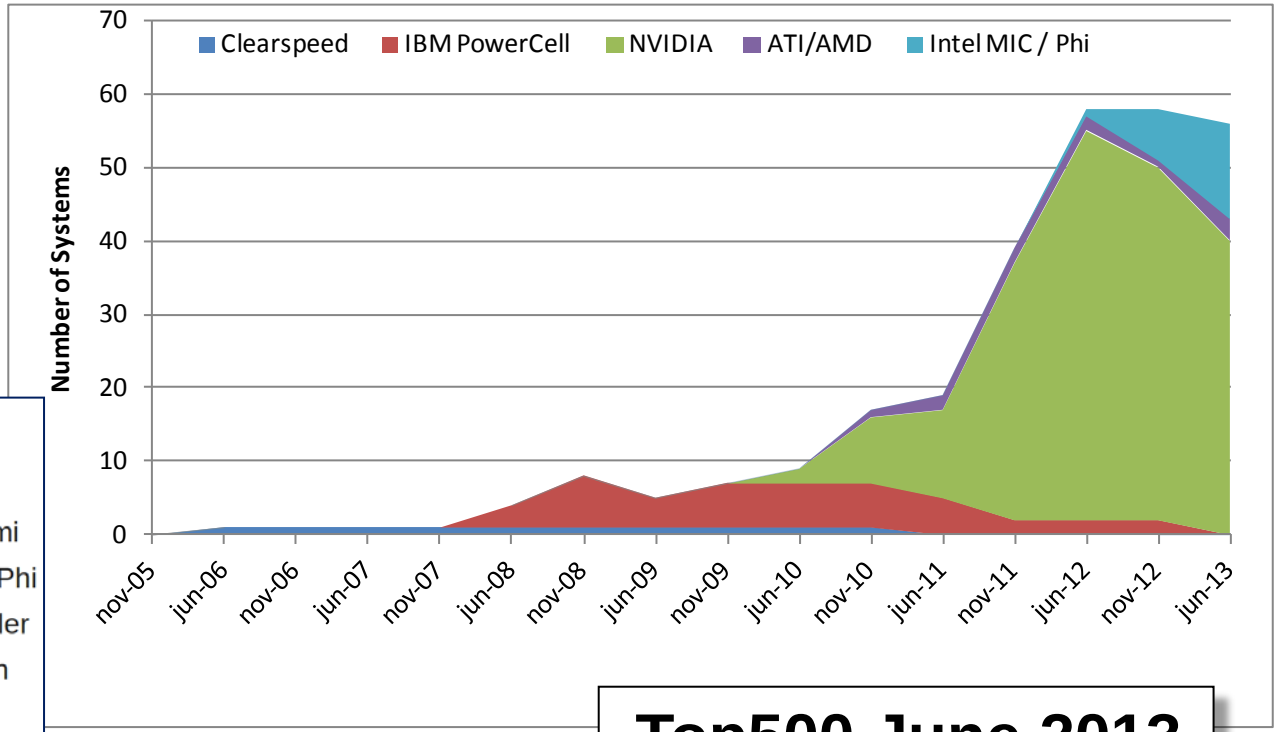
Current GPU computing facilities

- GPU computing defines all the technological issues for using the GPU computational power for executing general purpose applications
- GPU computing has experienced a remarkable growth in the last years

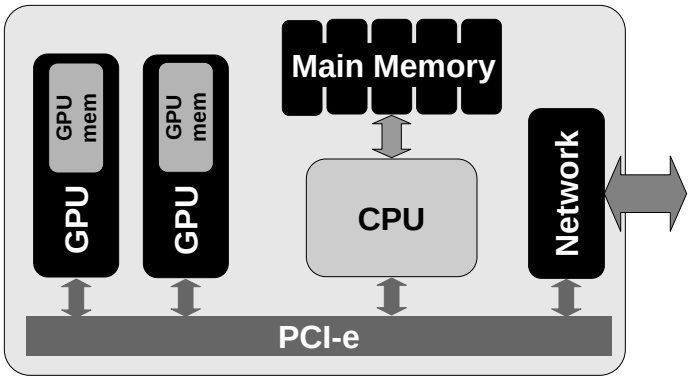


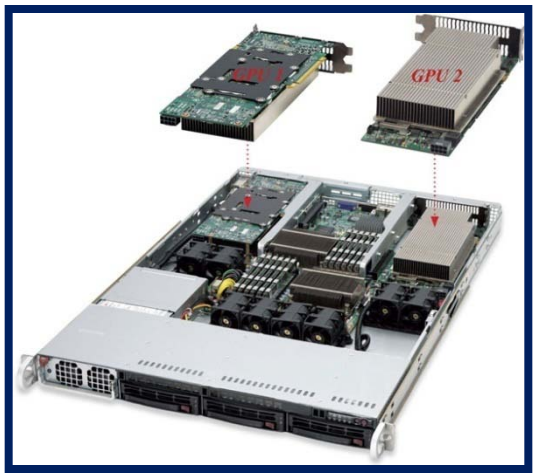


Top500 June 2013

Current GPU computing facilities

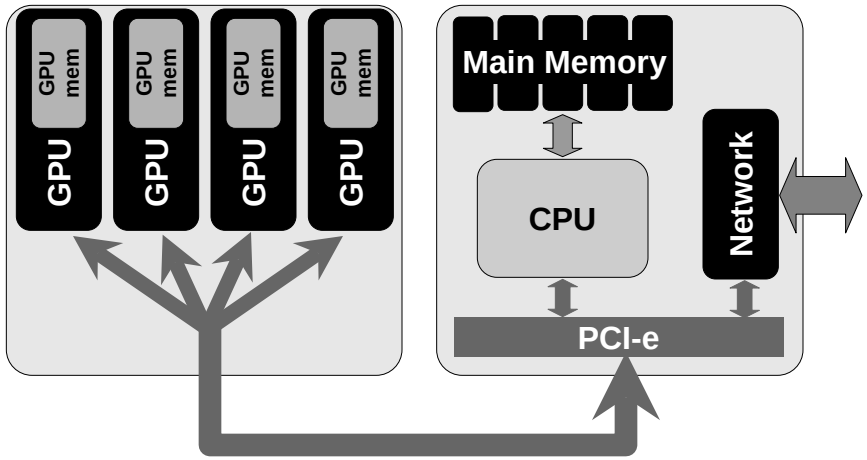
The basic building block is a node with one or more GPUs





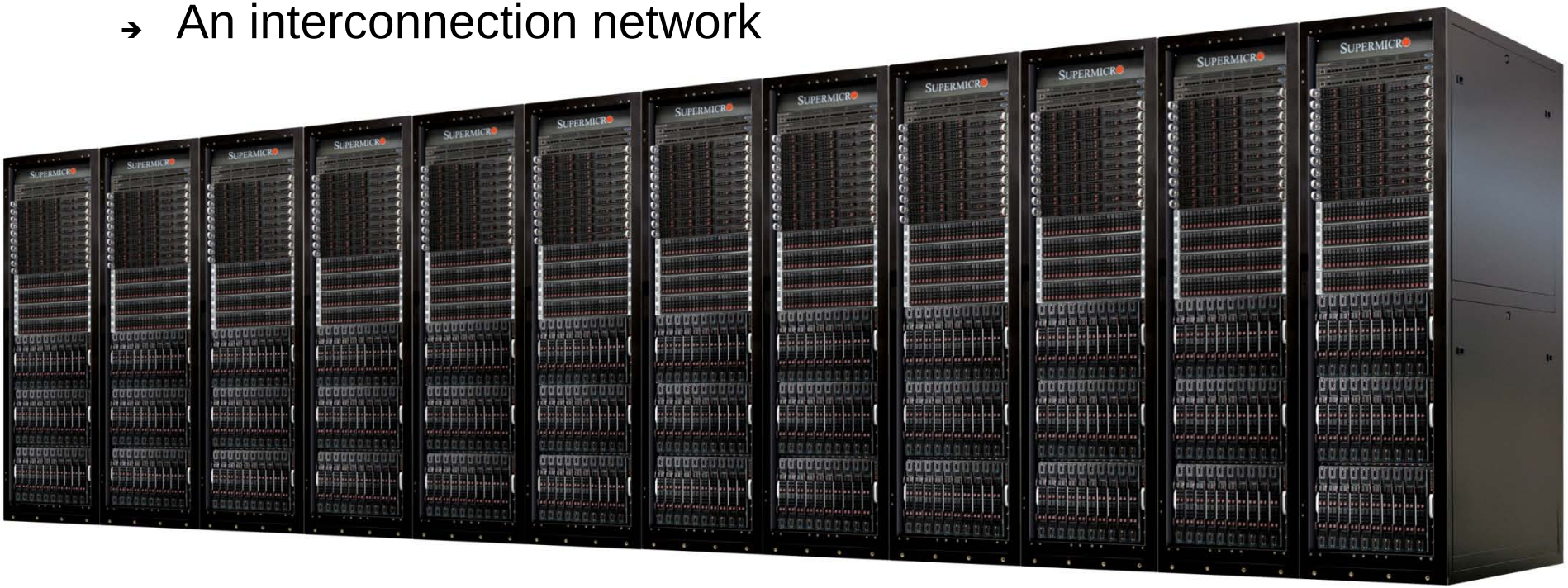
GPUs inside the CPU box

GPUs outside the CPU box



Current GPU computing facilities

- From the programming point of view:
  - A set of nodes, each one with:
    - one or more CPUs (probably with several cores per CPU)
    - one or more GPUs (typically between 1 and 4)
    - disjoint memory spaces for each GPU and the CPUs
  - An interconnection network



Current GPU computing facilities

- For **some kinds of code** the use of GPUs brings huge benefits in terms of performance and energy
  - There must be **data parallelism** in the code: this is the only way to take benefit from the hundreds of processors within a GPU
- Different scenarios from the point of view of the application:
  - Low level of data parallelism
  - High level of data parallelism
  - Moderate level of data parallelism
  - Applications for multi-GPU computing
    - Leveraging up to the 4 GPUs inside the node

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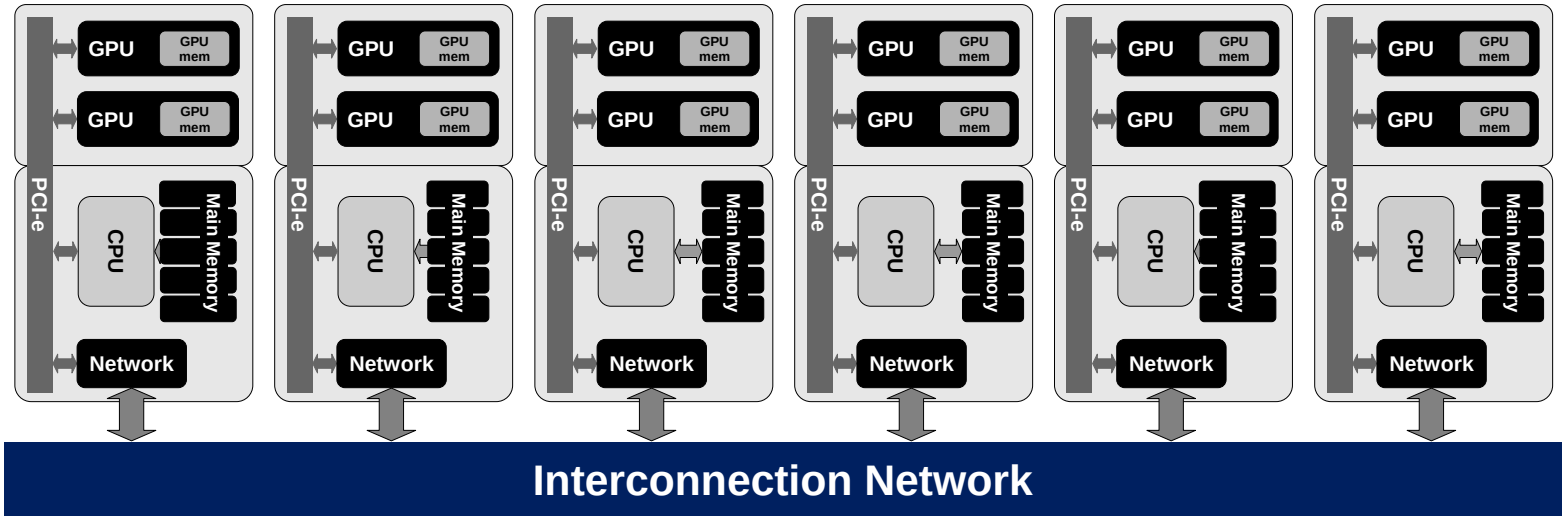
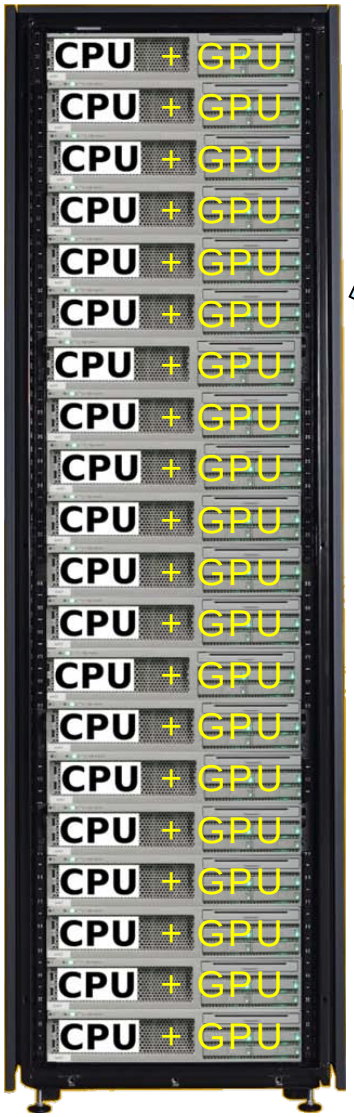
How GPU virtualization adds value

- A GPU computing facility is usually a set of independent self-contained nodes that leverage the shared-nothing approach
  - Nothing is directly shared among nodes (MPI required for aggregating computing resources within the cluster)
  - GPUs can only be used within the node they are attached to



How GPU virtualization adds value



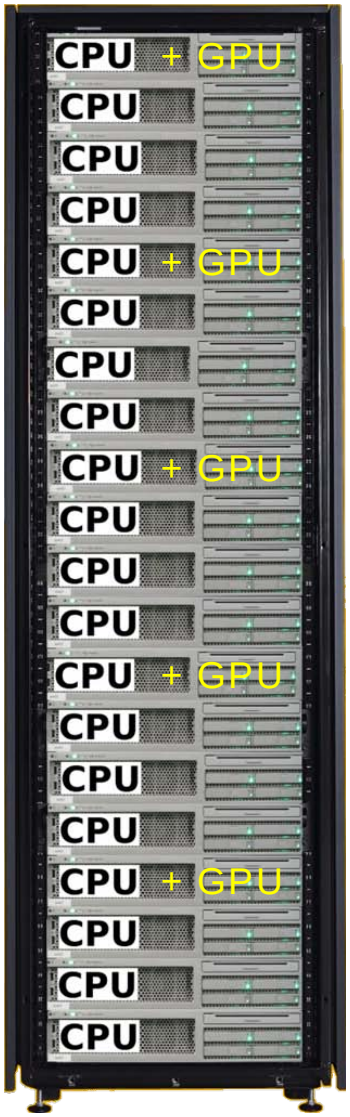
Current trend in GPU deployment

CONCERNS:

- Multi-GPU applications running on a subset of nodes cannot make use of the tremendous GPU resources available at other cluster nodes (even if they are idle)
- For applications with moderate levels of data parallelism, many GPUs in the cluster may be idle for long periods of time

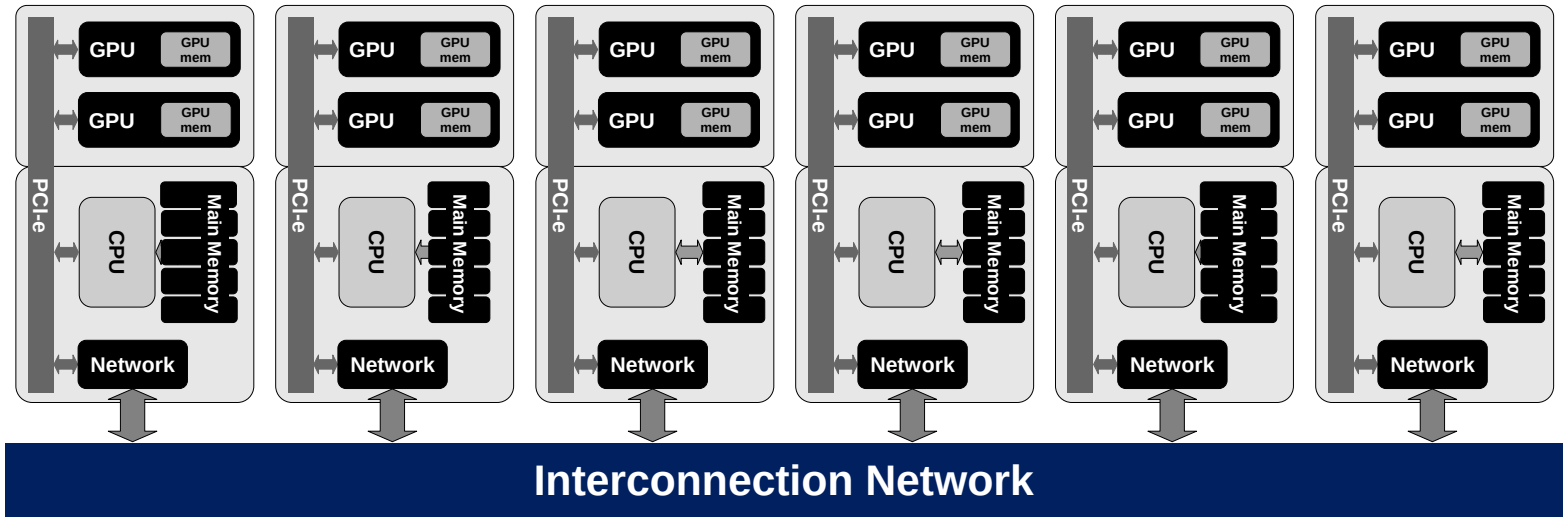
How GPU virtualization adds value

- A way of addressing the first concern is by **sharing** the GPUs present in the cluster among all the nodes. For the second concern, once GPUs are shared, their amount can be **reduced**
- This would increase GPU utilization, also lowering power consumption, at the same time that initial acquisition costs are reduced
- This new configuration requires:
  1) A way of seamlessly sharing GPUs across nodes in the cluster (GPU virtualization)
  2) Enhanced job schedulers that take into account the new GPU configuration



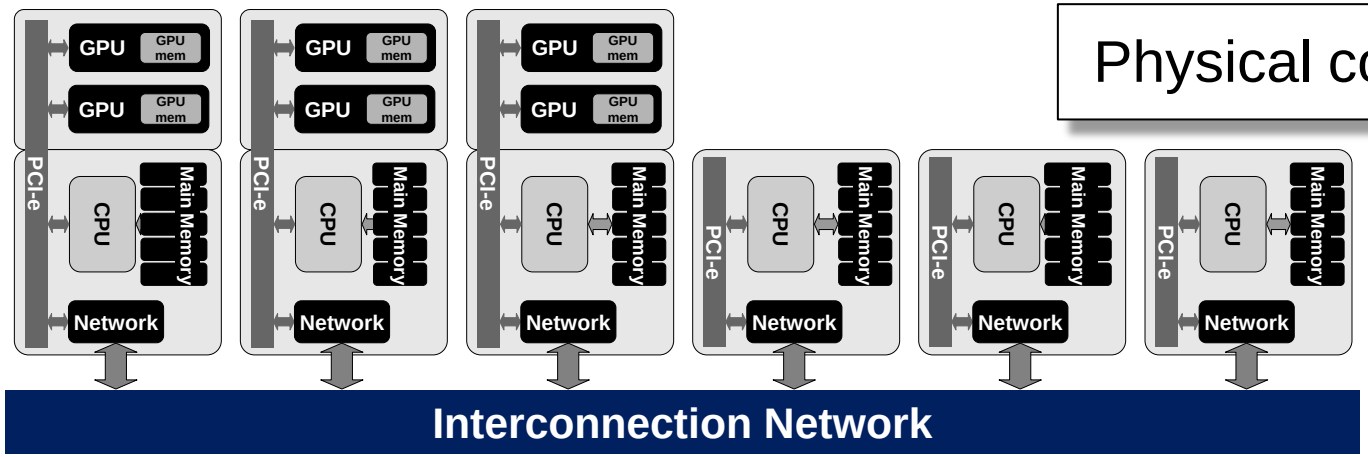
How GPU virtualization adds value

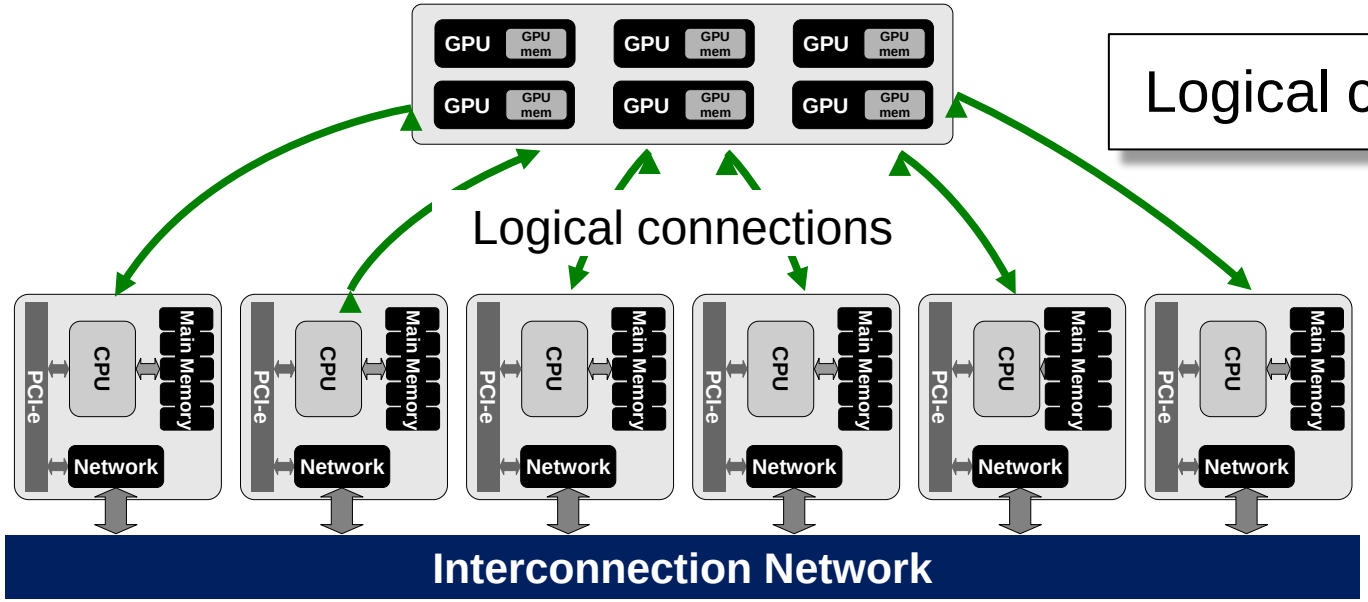
- In summary, **GPU virtualization allows a new vision** of a GPU deployment, moving from the usual cluster configuration:



to the following one ….

How GPU virtualization adds value

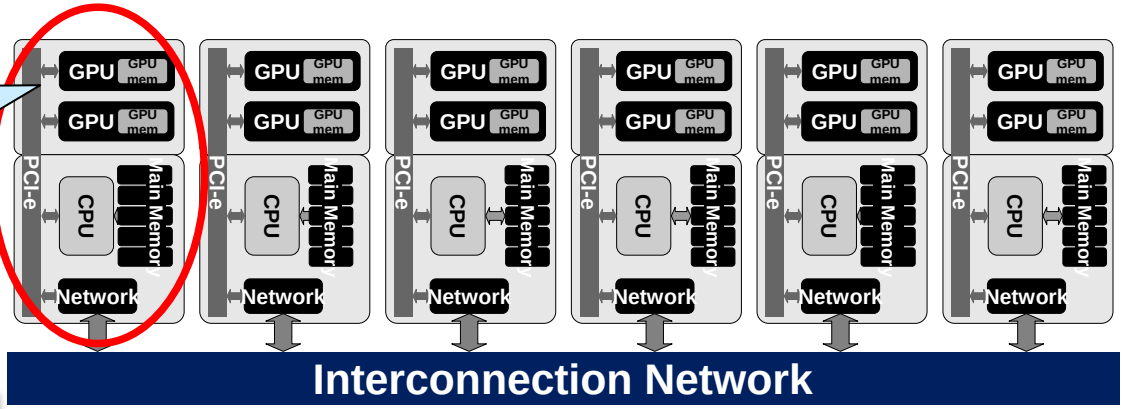




How GPU virtualization adds value

- GPU virtualization is also useful for multi-GPU applications

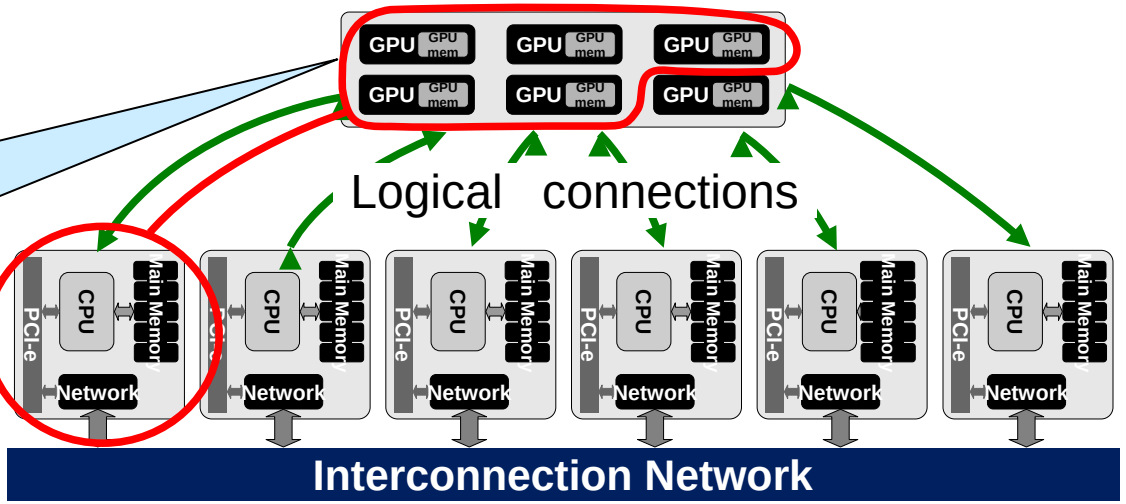
Only the GPUs in the node can be provided to the application



Without GPU virtualization

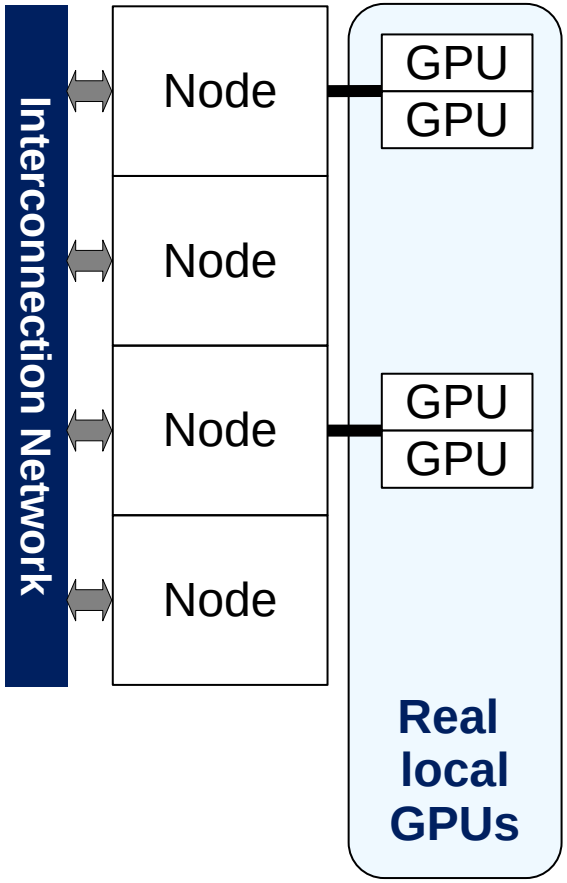
With GPU virtualization

Many GPUs in the cluster can be provided to the application

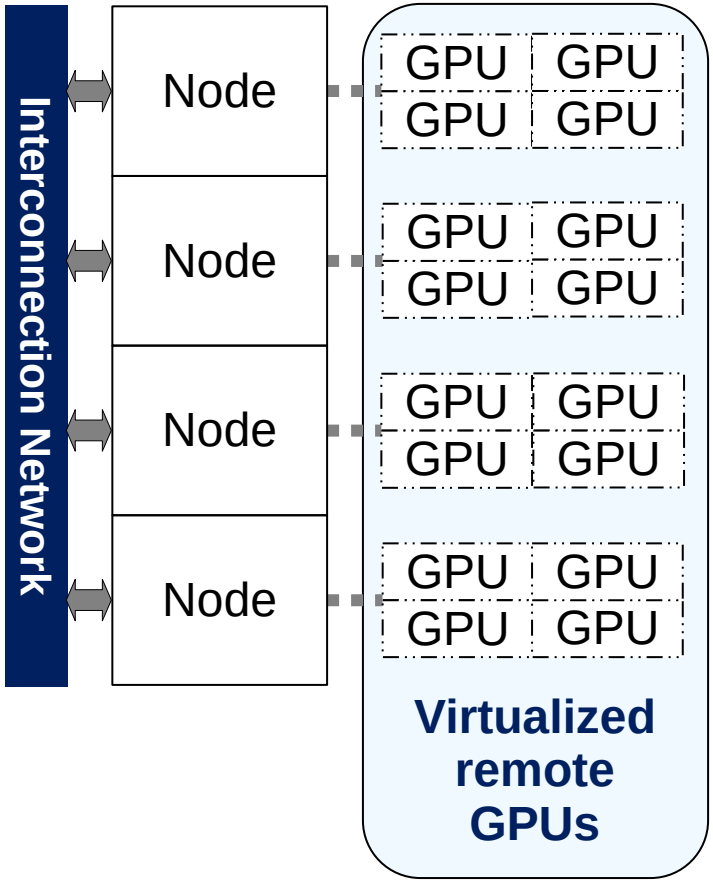


How GPU virtualization adds value

- GPU virtualization allows all nodes to access all GPUs



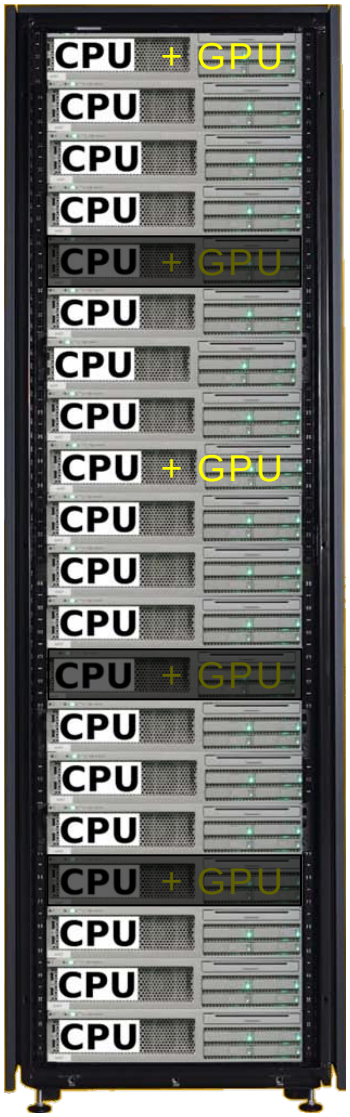
Physical configuration



Logical configuration

How GPU virtualization adds value

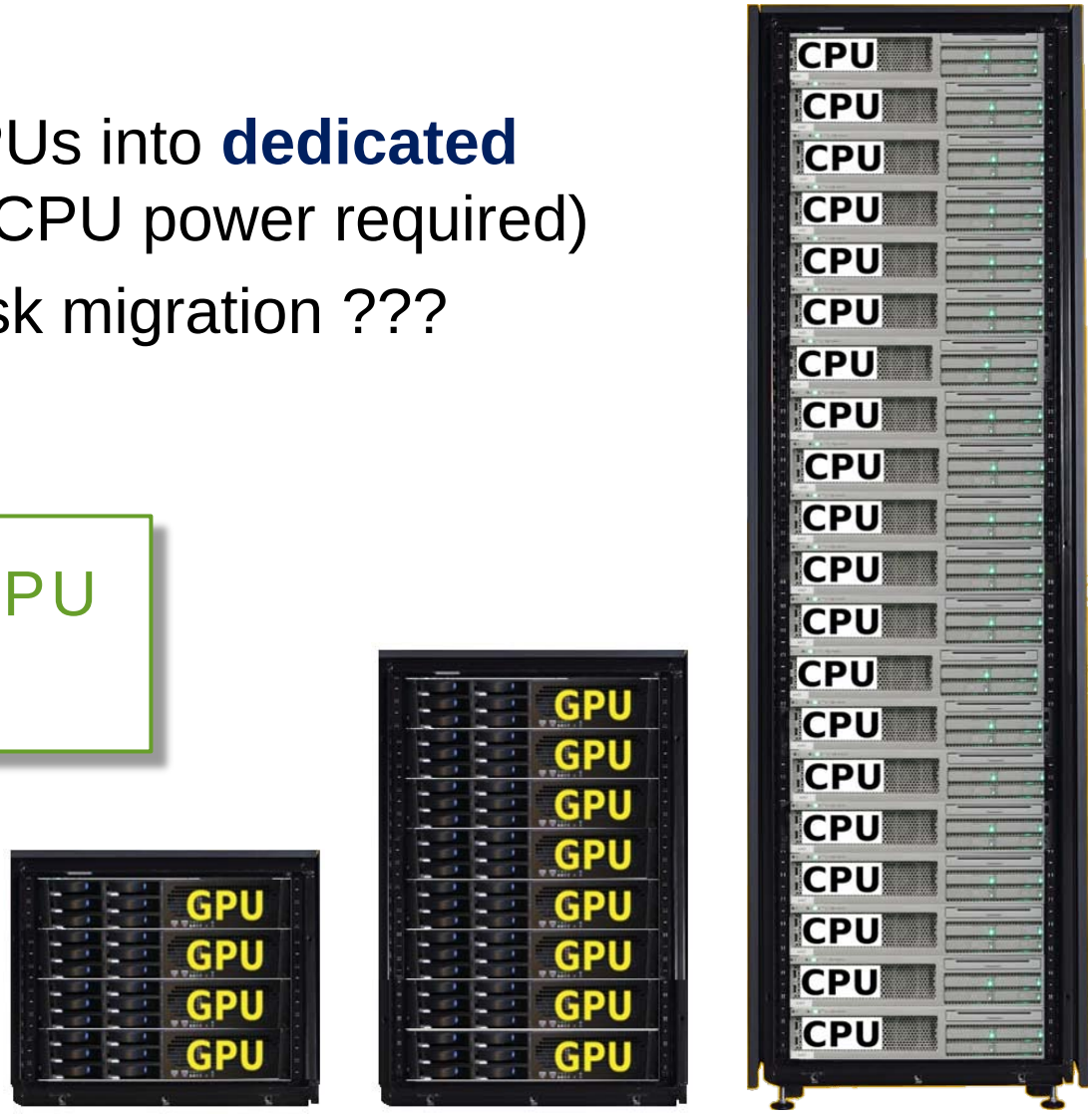
- One step further:
  - enhancing the scheduling process so that GPU servers are put into low-power sleeping modes as soon as their acceleration features are not required



How GPU virtualization adds value

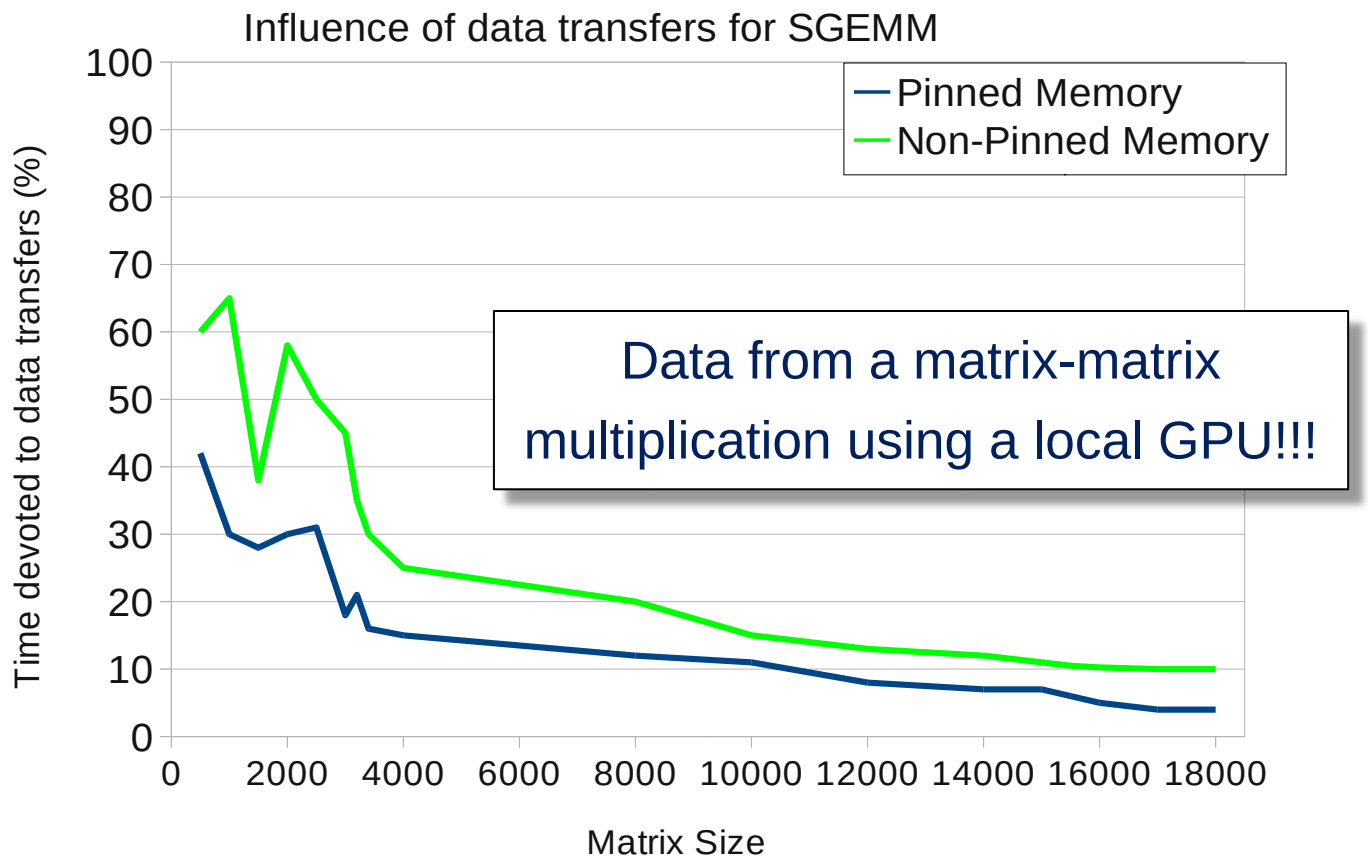
- Going even beyond:
  - consolidating GPUs into **dedicated GPU boxes** (no CPU power required)
  - allowing GPU task migration ???

TRUE GREEN GPU COMPUTING



How GPU virtualization adds value

- Main GPU virtualization drawback is the increased latency and reduced bandwidth to the remote GPU



How GPU virtualization adds value

- Several efforts have been made regarding GPU virtualization during the last years:

• **rCUDA**	**(CUDA 5.0)**	**Publicly available**
• GVirtuS	(CUDA 3.2)	
• DS-CUDA	(CUDA 4.1)	
• vCUDA	(CUDA 1.1)	**NOT publicly available**
• GViM	(CUDA 1.1)	
• GridCUDA	(CUDA 2.3)	
• V-GPU	(CUDA 4.0)	

How GPU virtualization adds value

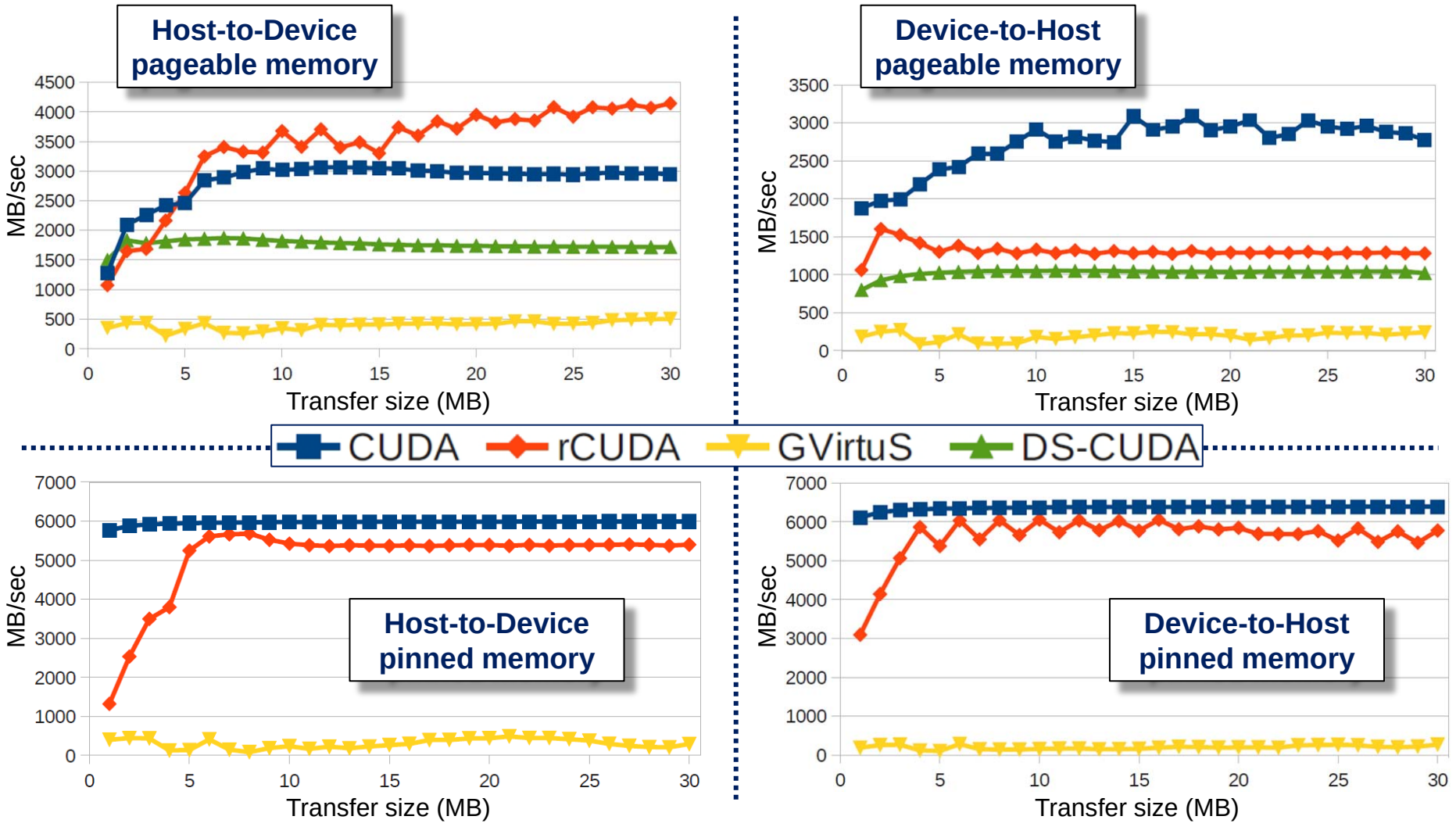
- **Performance comparison** of GPU virtualization solutions:
  - Intel Xeon E5-2620 (6 cores) 2.0 GHz (SandyBrigde architecture)
  - GPU NVIDIA Tesla K20
  - Mellanox ConnectX-3 single-port InfiniBand Adapter (FDR)
  - SX6025 Mellanox switch
  - CentOS 6.3 + Mellanox OFED 1.5.3

Latency (measured by transferring 64 bytes)

	Pageable H2D	**Pinned H2D**	**Pageable D2H**	**Pinned D2H**
CUDA	34,3	4,3	16,2	5,2
rCUDA	94,5	23,1	292,2	6,0
GVirtuS	184,2	200,3	168,4	182,8
DS-CUDA	45,9	-	26,5	-

How GPU virtualization adds value

- Bandwidth of a copy between GPU and CPU memories



How GPU virtualization adds value

- rCUDA has been successfully tested with the following applications:
  - NVIDIA CUDA SDK Samples
  - LAMMPS
  - WideLM
  - CUDASW++
  - OpenFOAM
  - HOOMDBlue
  - mCUDA-MEME
  - GPU-Blast
  - Gromacs

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Basics of the rCUDA framework

rCUDA remote CUDA

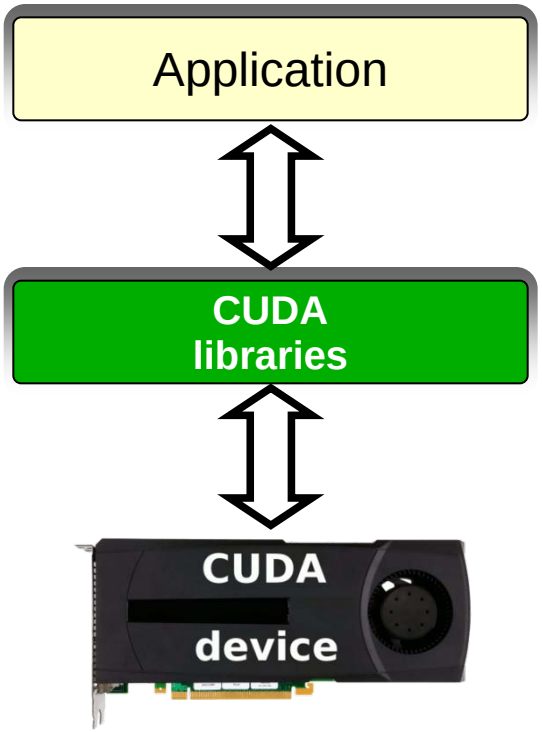
A framework enabling a CUDA-based application running in one (or some) node(s) to access GPUs in other nodes

It is useful for:

- Moderate level of data parallelism
- Applications for multi-GPU computing

Basics of the rCUDA framework

CUDA application



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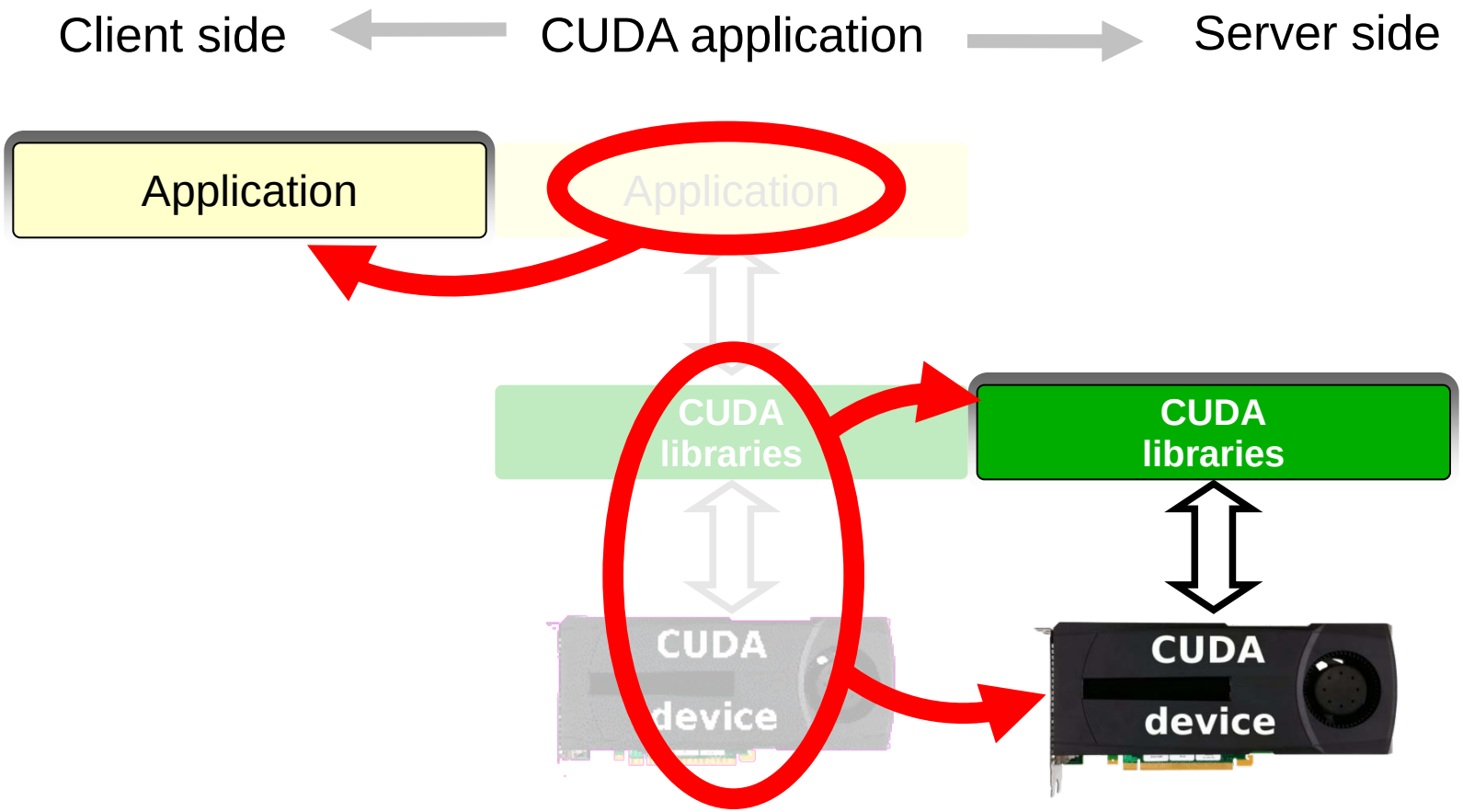

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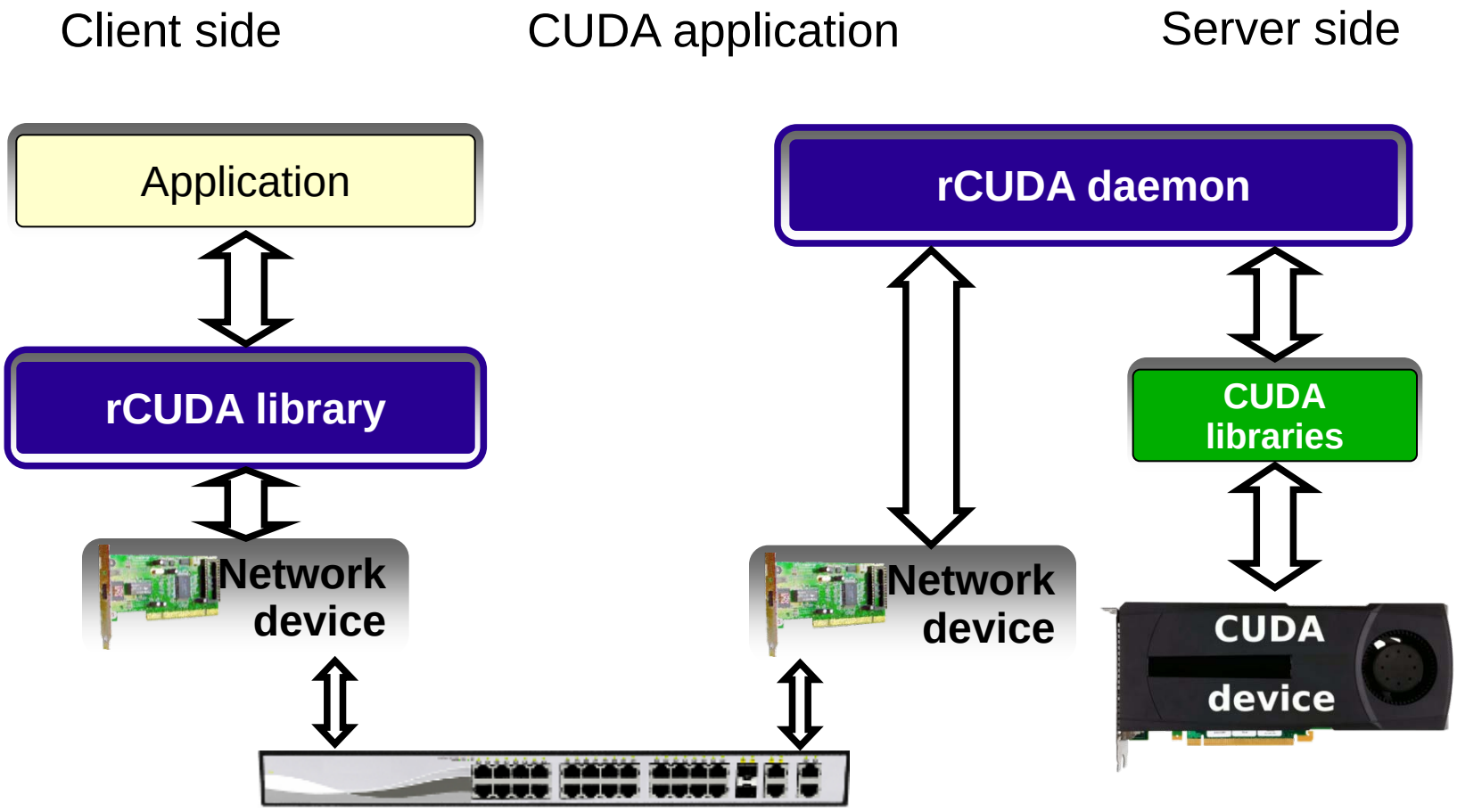

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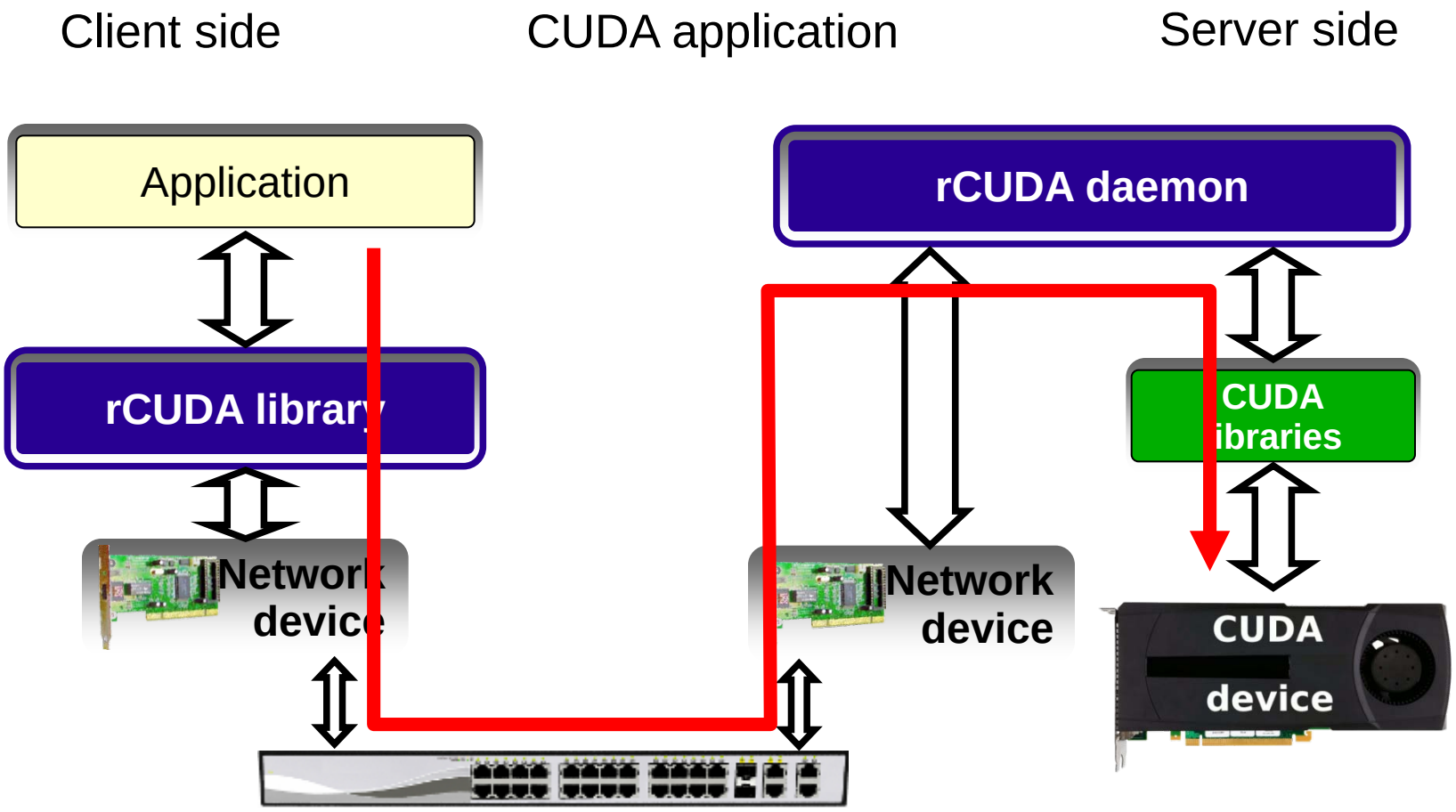

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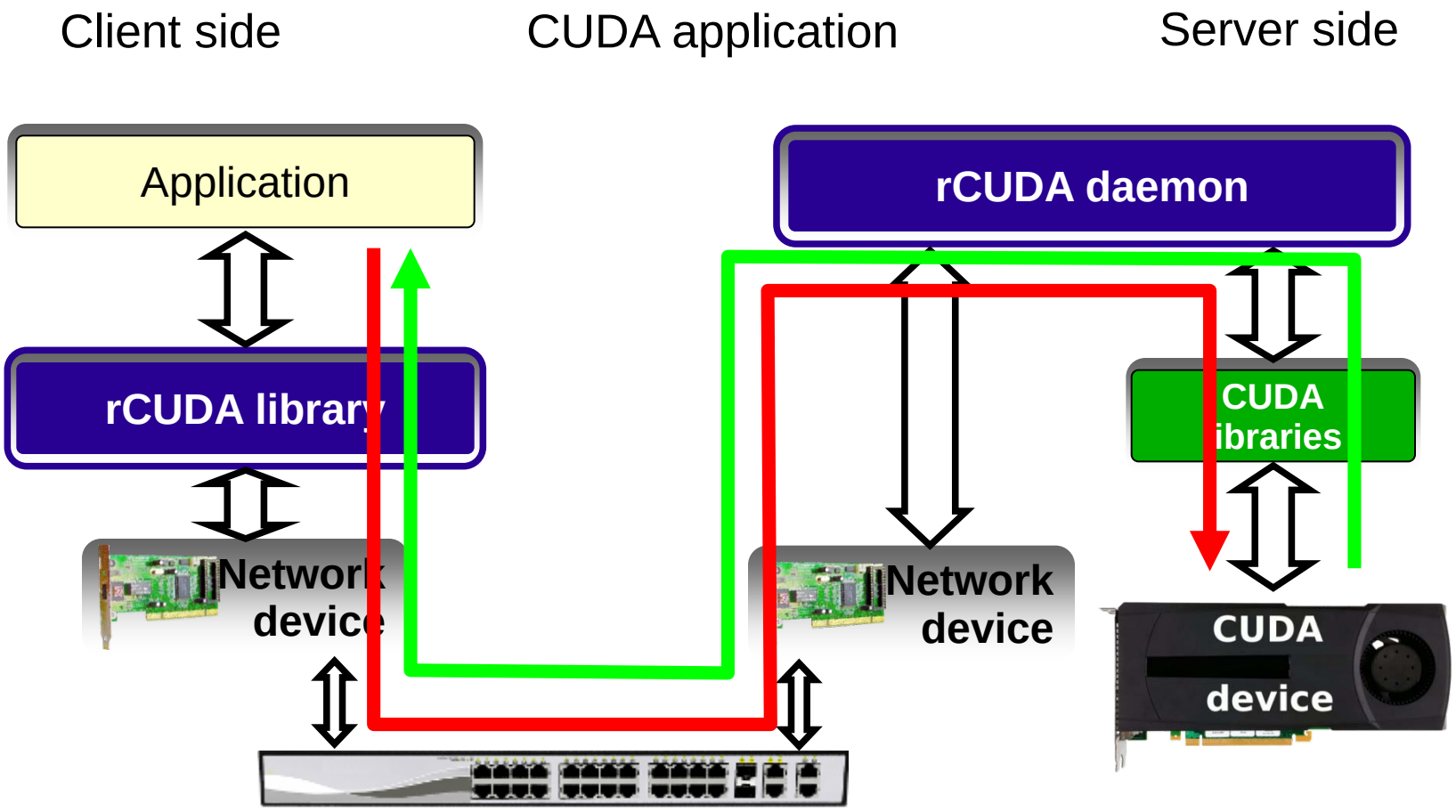
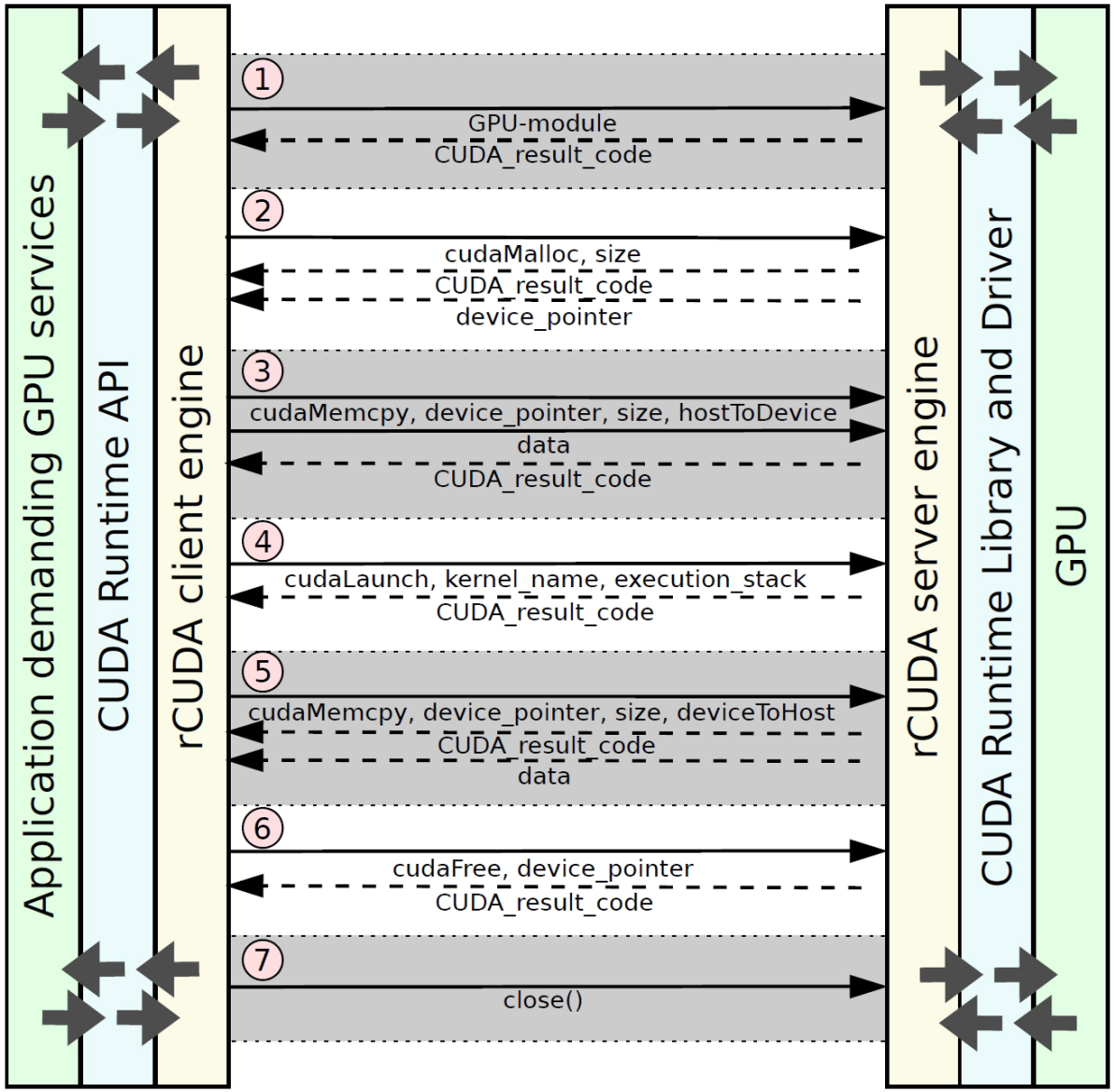


Basics of the rCUDA framework

rCUDA uses a proprietary communication protocol

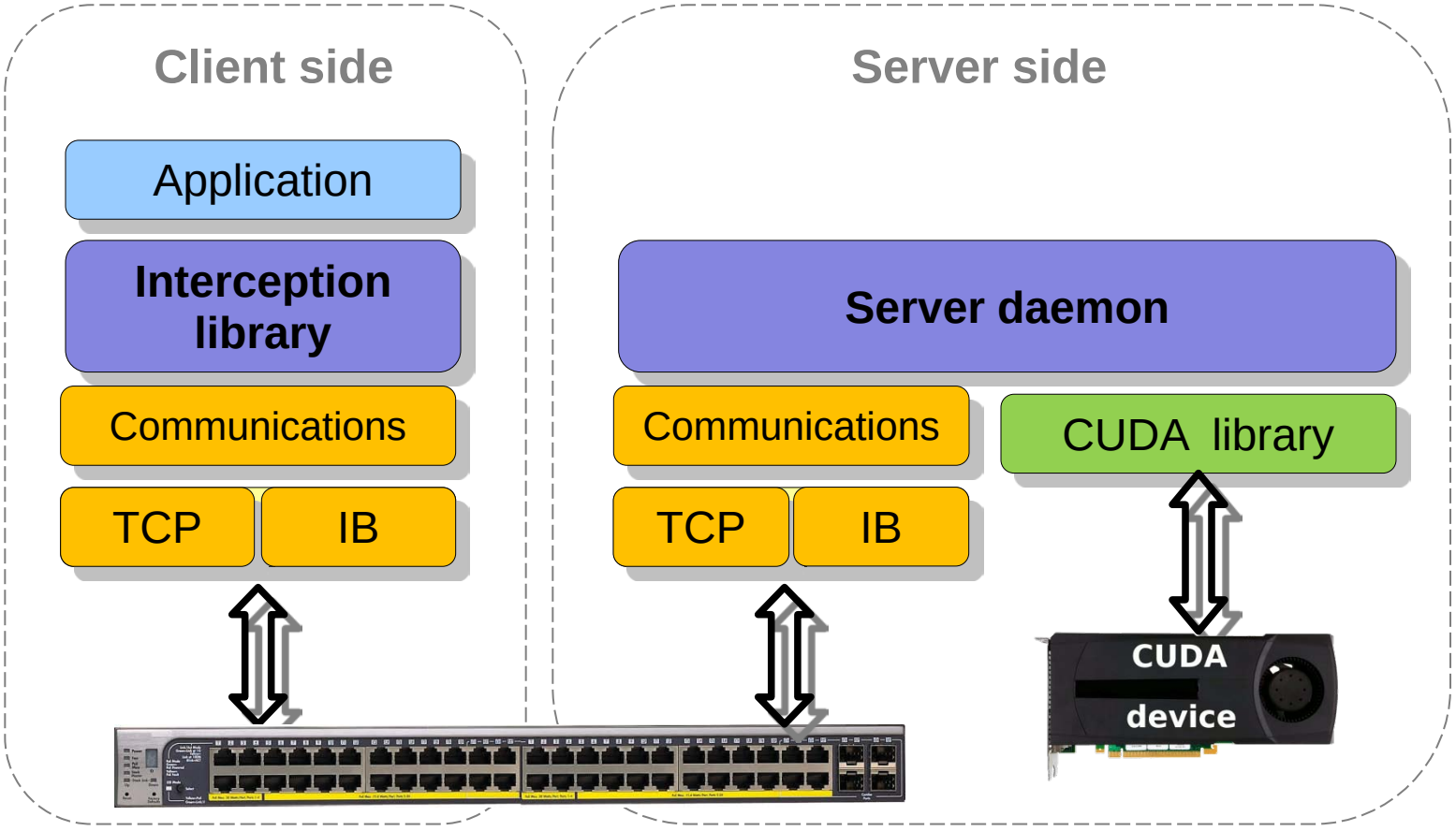
Example:

1) initialization
2) memory allocation on the remote GPU
3) CPU to GPU memory transfer of the input data
4) kernel execution
5) GPU to CPU memory transfer of the results
6) GPU memory release
7) communication channel closing and server process finalization



Basics of the rCUDA framework

- rCUDA features **a modular architecture**

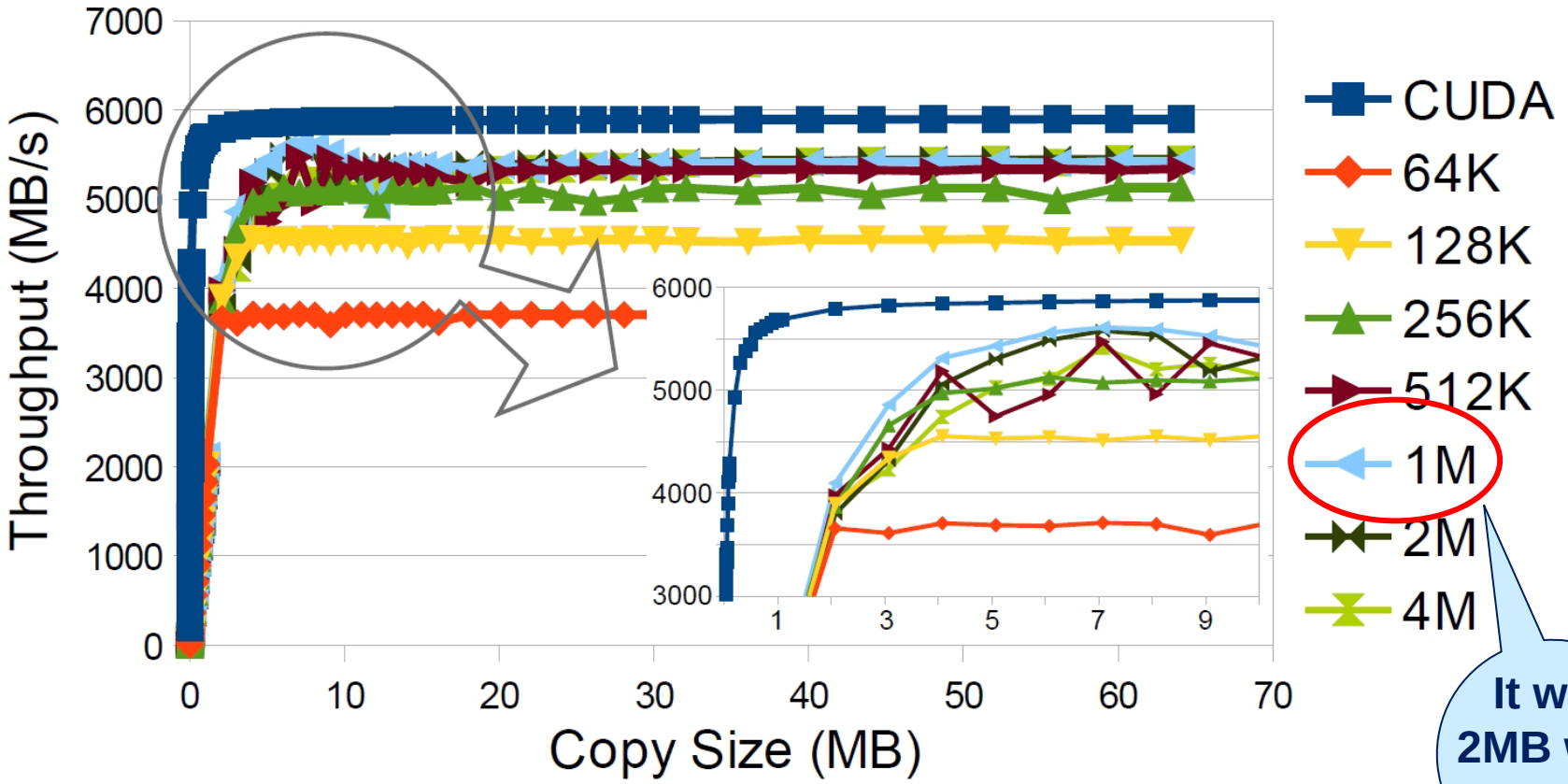


Basics of the rCUDA framework

- rCUDA features **optimized communications:**
  - Use of GPUDirect to avoid unnecessary memory copies
  - Pipeline to improve performance
  - Preallocated pinned memory buffers
  - Optimal pipeline block size

Basics of the rCUDA framework

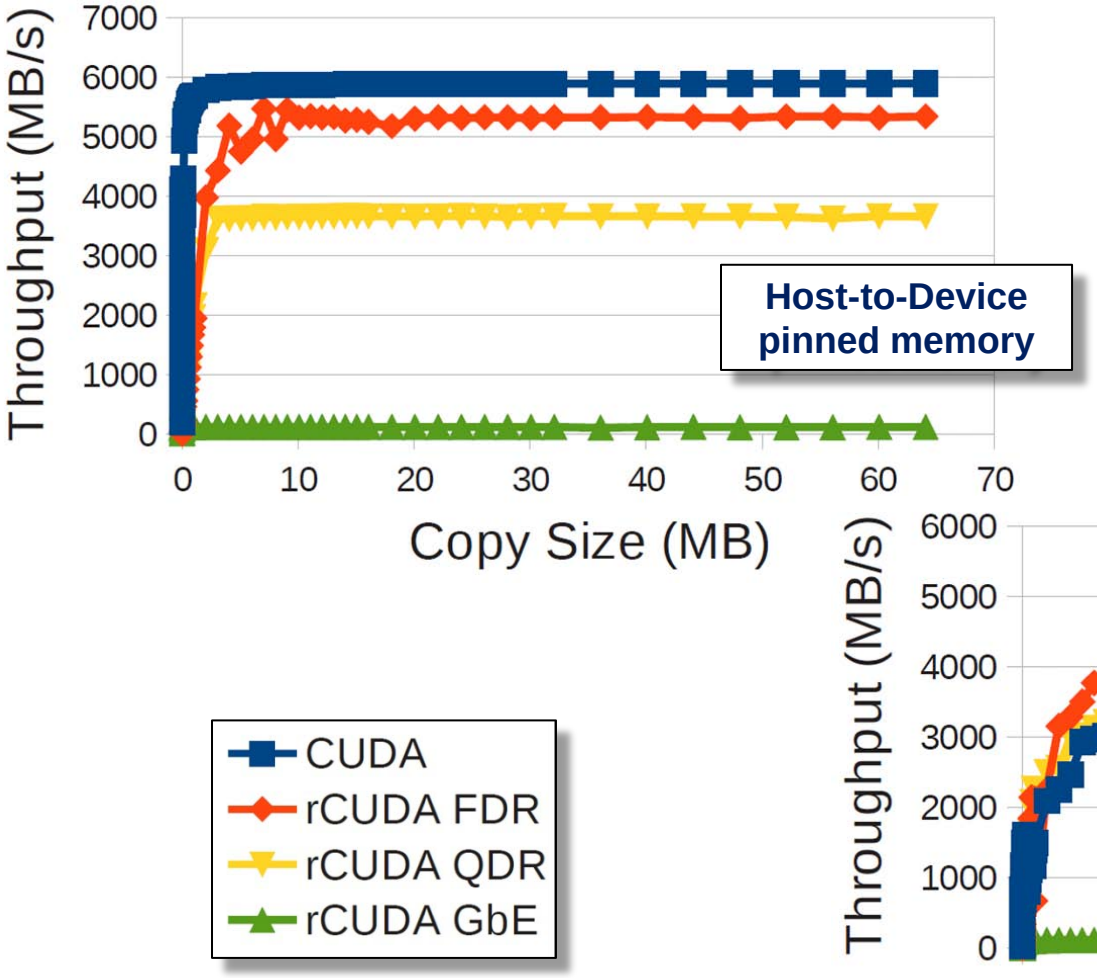
- Pipeline block size for InfiniBand FDR

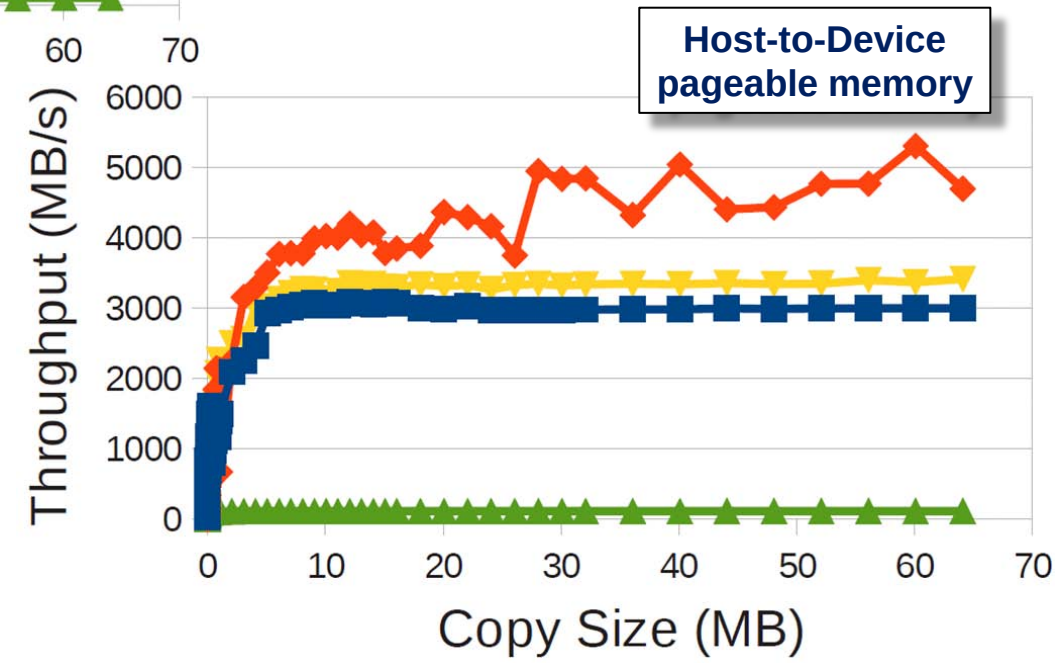


- NVIDIA Tesla K20; Mellanox ConnectX-3 + SX6025 Mellanox switch

Basics of the rCUDA framework

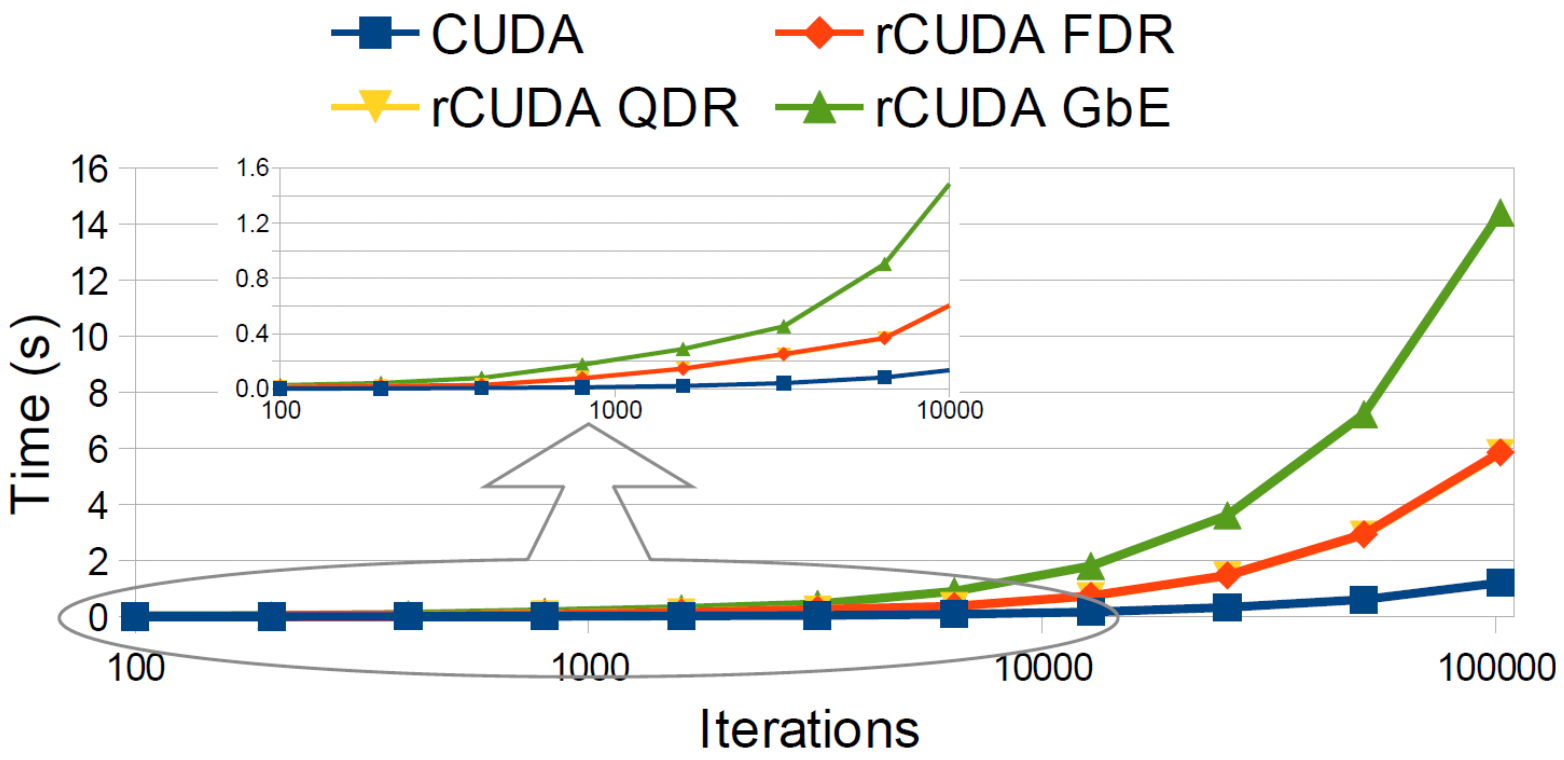
- Bandwidth of a copy between GPU and CPU memories





Basics of the rCUDA framework

- Latency study: copy a small dataset (64 bytes)



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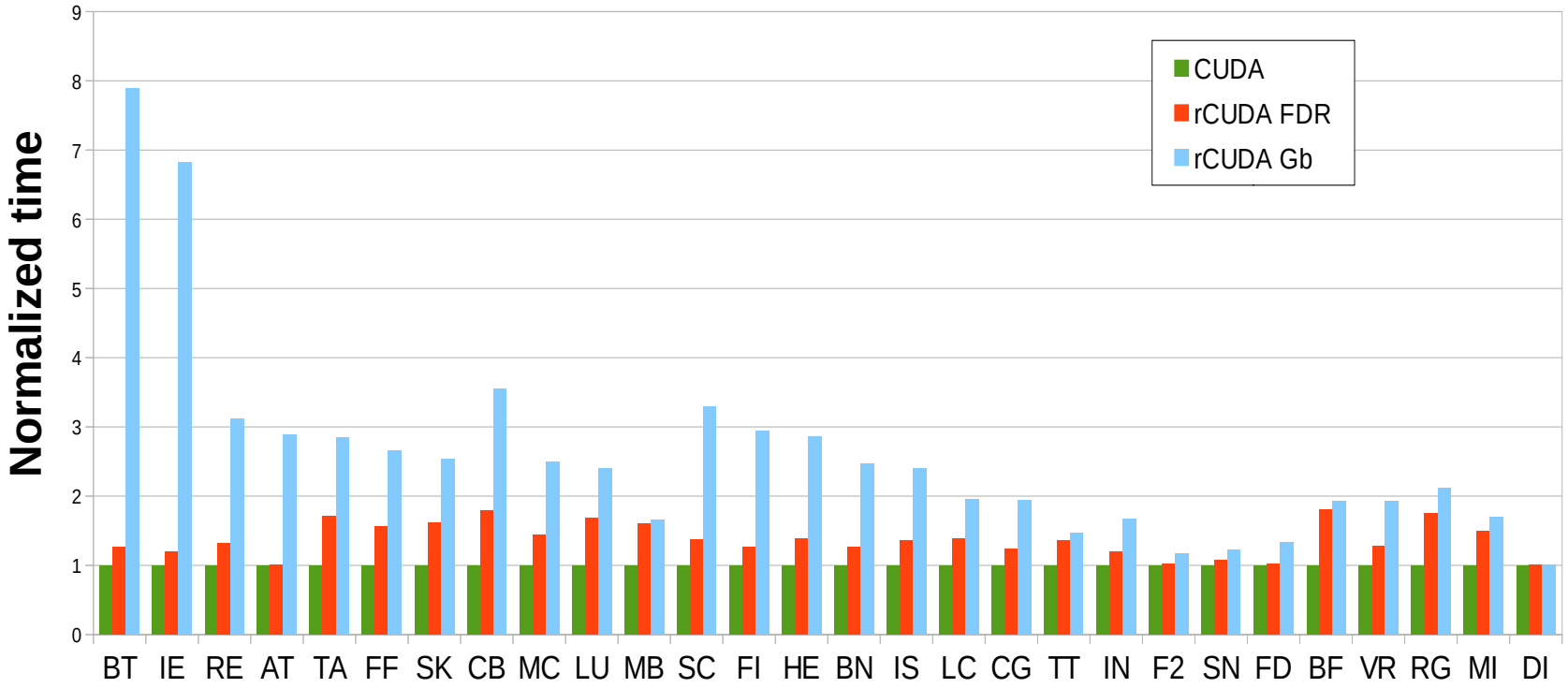
Performance of the rCUDA framework

- Test system:
  - Intel Xeon E5-2620 (6 cores) 2.0 GHz (SandyBrigde architecture)
  - GPU NVIDIA Tesla K20
  - Mellanox ConnectX-3 single-port InfiniBand Adapter (FDR)
  - SX6025 Mellanox switch
  - Cisco switch SLM2014 (1Gbps Ethernet)
  - CentOS 6.3 + Mellanox OFED 1.5.3

Performance of the rCUDA framework

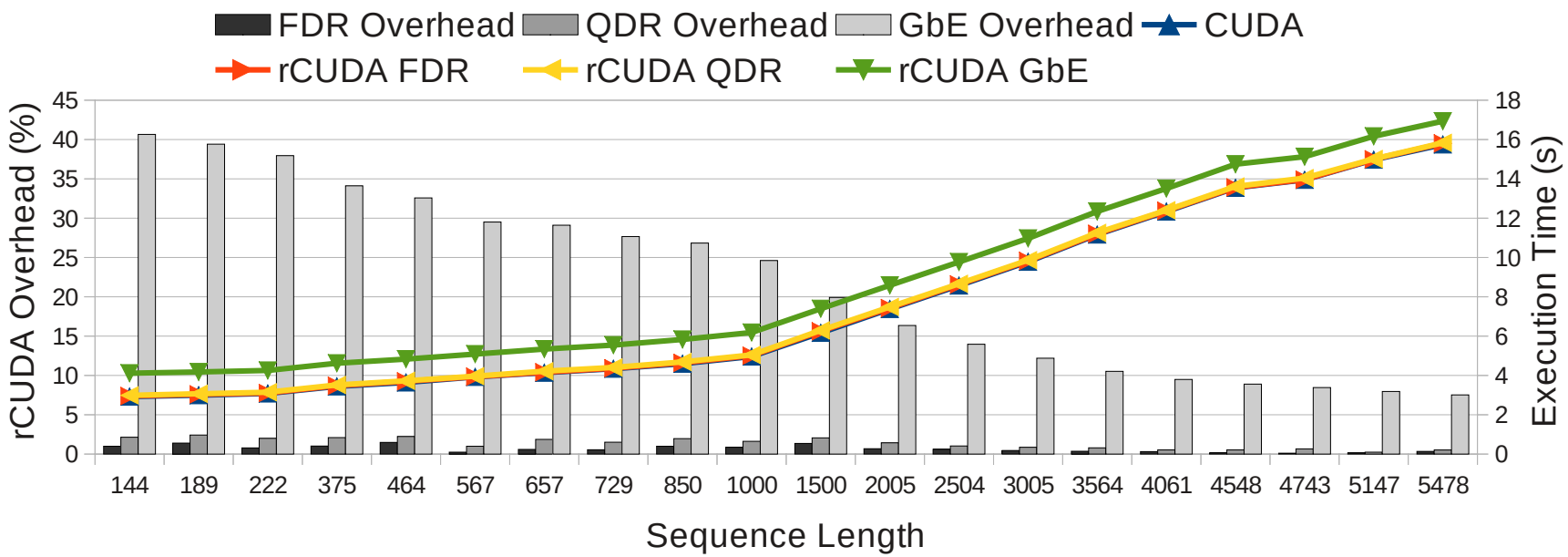
- Test CUDA SDK examples



Performance of the rCUDA framework

- CUDASW++

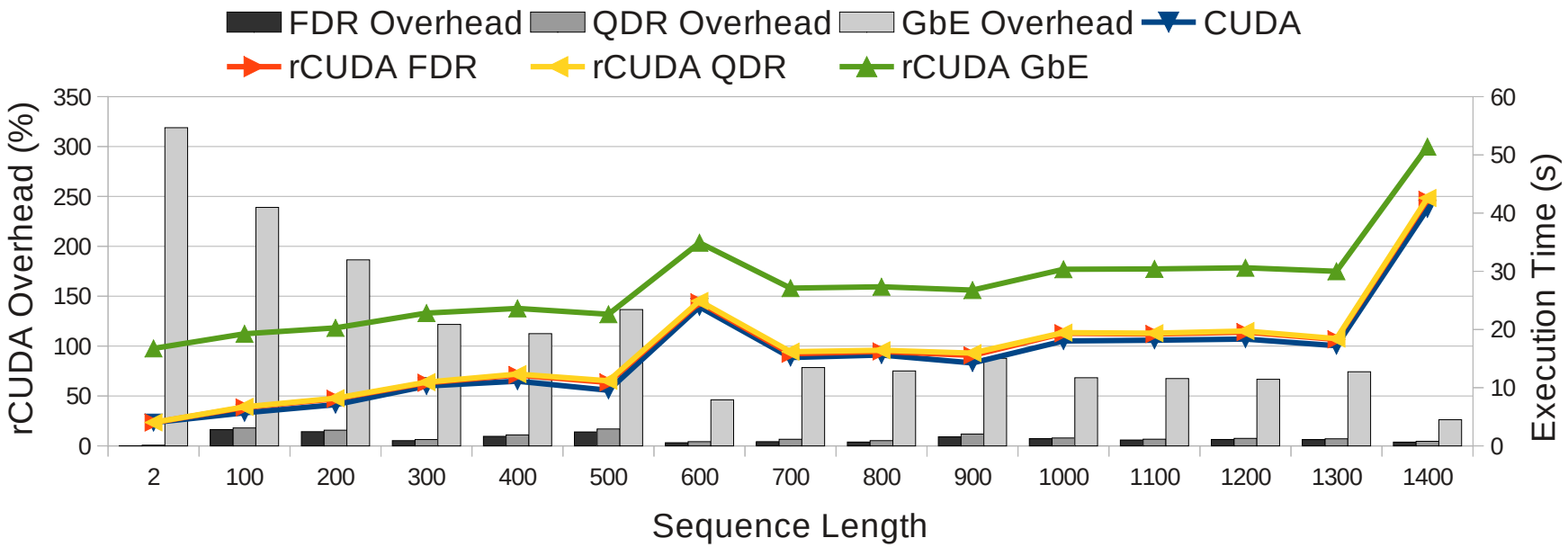
  Bioinformatics software for Smith-Waterman protein database searches



Performance of the rCUDA framework

- GPU-Blast

  Accelerated version of the NCBI-BLAST (Basic Local Alignment Search Tool), a widely used bioinformatics tool

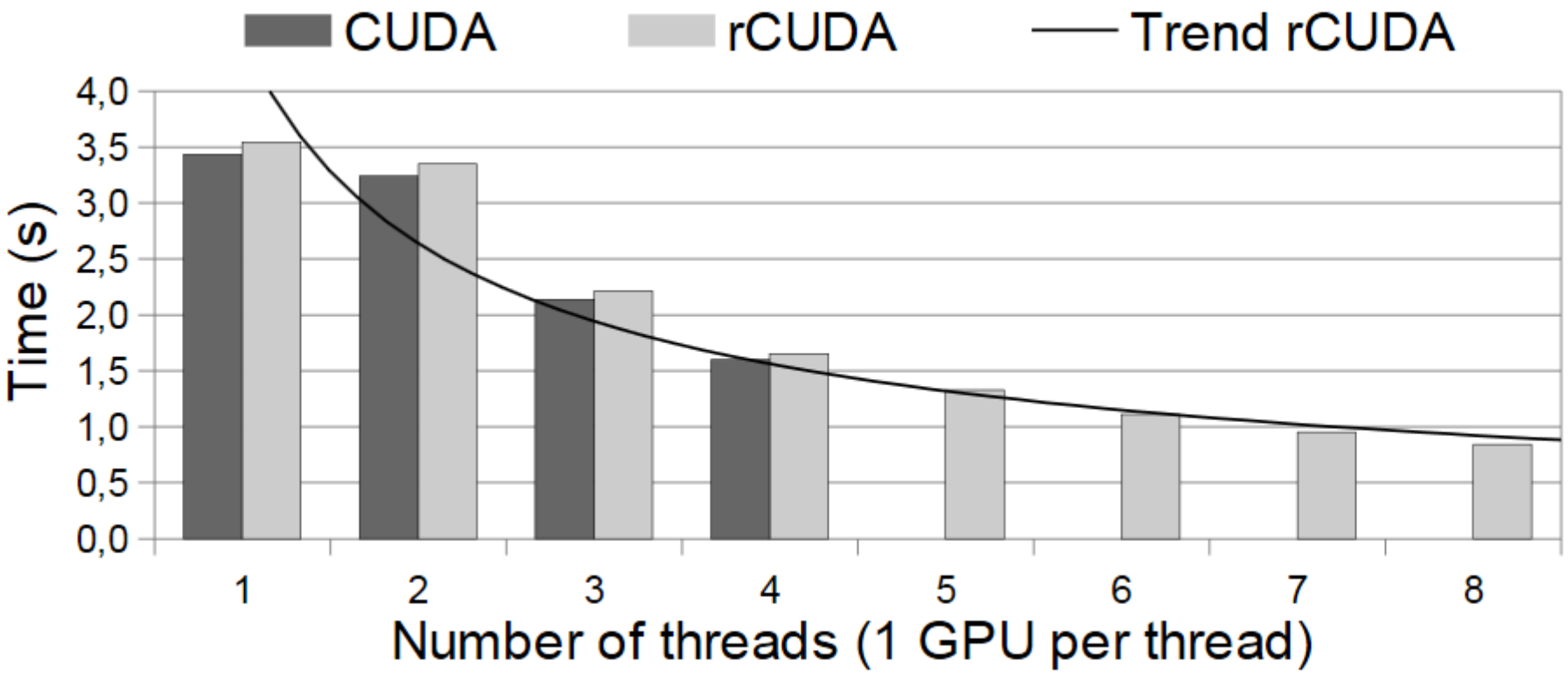


Performance of the rCUDA framework

- Test system for MultiGPU
  - For CUDA tests one node with:
    - 2 Quad-Core Intel Xeon E5440 processors
    - Tesla S2050 (4 Tesla GPUs)
    - Each thread (1-4) uses one GPU
  - For rCUDA tests 8 nodes with:
    - 2 Quad-Core Intel Xeon E5520 processors
    - 1 NVIDIA Tesla C2050
    - InfiniBand QDR
    - Test running in one node and using up to all the GPUs of the others
    - Each thread (1-8) uses one GPU

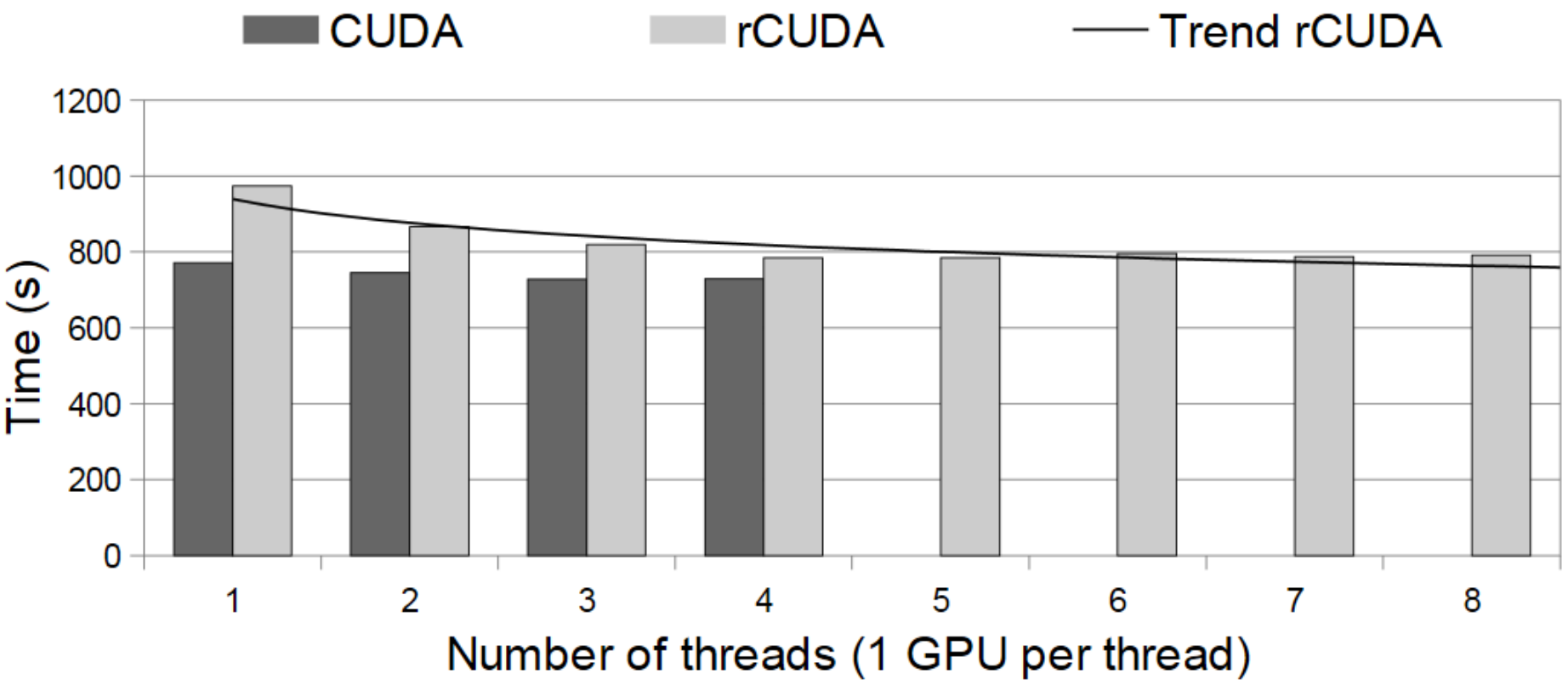
Performance of the rCUDA framework

- MonteCarlo MultiGPU (from NVIDIA SDK)



Performance of the rCUDA framework

- GEMM MultiGPU
  - using **libflame:** high performance dense linear algebra library http://www.cs.utexas.edu/~flame/web/



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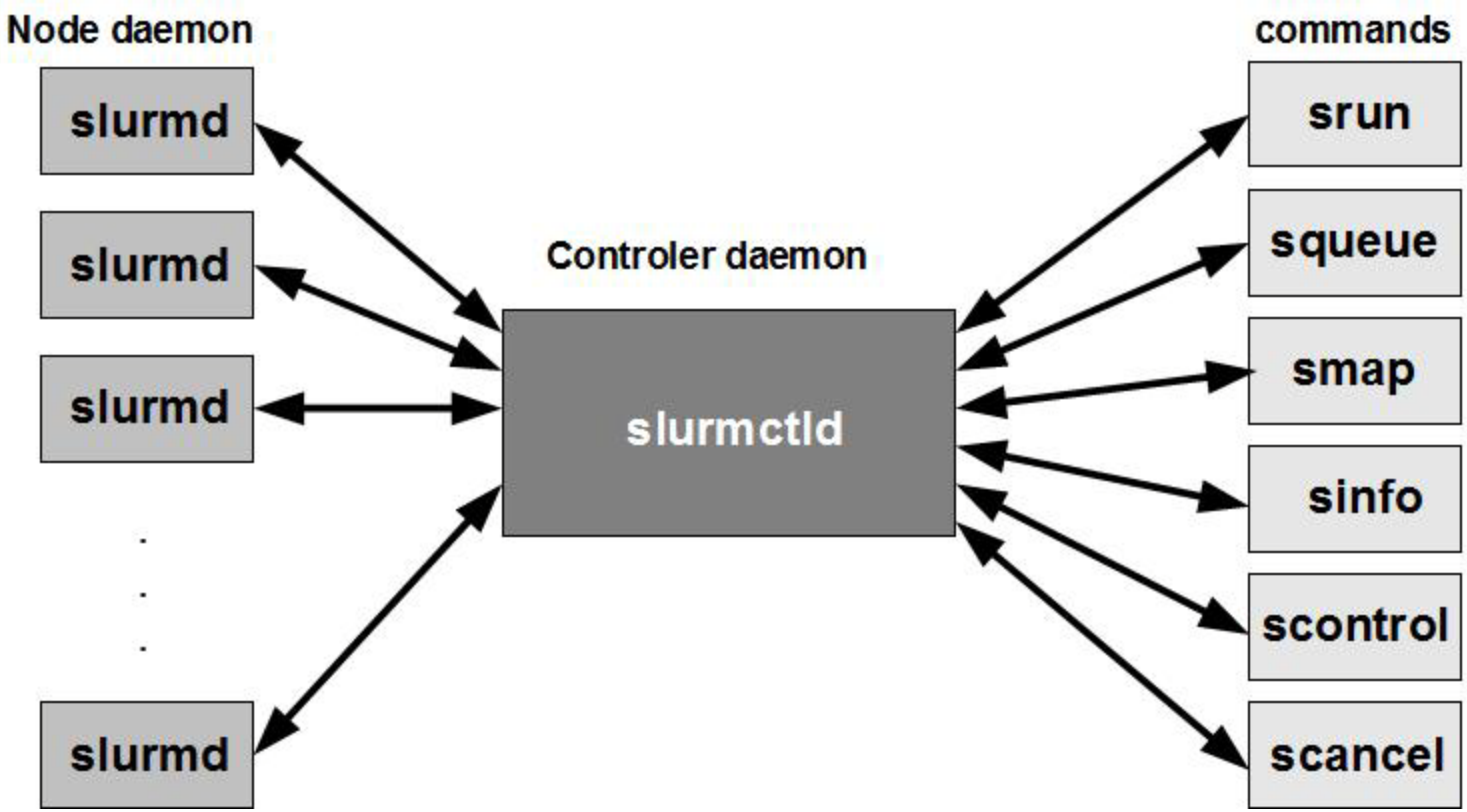
Integrating rCUDA with SLURM

- SLURM (Simple Linux Utility for Resource Management) job scheduler
- Does not understand about virtualized GPUs
- Add a new GRES (general resource) in order to manage virtualized GPUs
- Where the GPUs are in the system is completely transparent to the user
- In the job script or in the submission command, the user specifies the number of rGPUs (remote GPUs) required by the job

Integrating rCUDA with SLURM



Integrating rCUDA with SLURM

slurm.conf

```
ClusterName=rcu
…
GresTypes=gpu,rgpu
…
NodeName=rcu16 NodeAddr=rcu16 CPUs=8 Sockets=1
       CoresPerSocket=4 ThreadsPerCore=2
       RealMemory=7990 Gres=rgpu:4,gpu:4
```

Integrating rCUDA with SLURM

scontrol show node

```
NodeName=rcu16 Arch=x86_64 CoresPerSocket=4
        CPUAlloc=0 CPUErr=0 CPUTot=8 Features=(null)
        Gres=rgpu:4,gpu:4
        NodeAddr=rcu16 NodeHostName=rcu16
        OS=Linux RealMemory=7682 Sockets=1
        State=IDLE ThreadsPerCore=2 TmpDisk=0 Weight=1
        BootTime=2013-04-24T18:45:35
        SlurmdStartTime=2013-04-30T10:02:04
```

Integrating rCUDA with SLURM

gres.conf

```
Name=rgpu File=/dev/nvidia0 Cuda=2.1 Mem=1535m
Name=rgpu File=/dev/nvidia1 Cuda=3.5 Mem=1535m
Name=rgpu File=/dev/nvidia2 Cuda=1.2 Mem=1535m
Name=rgpu File=/dev/nvidia3 Cuda=1.2 Mem=1535m
Name=gpu File=/dev/nvidia0
Name=gpu File=/dev/nvidia1
Name=gpu File=/dev/nvidia2
Name=gpu File=/dev/nvidia3
```

Integrating rCUDA with SLURM

Submit a job

```
$
$ srun -N1 --gres=rgpu:4:512M script.sh...
$
```

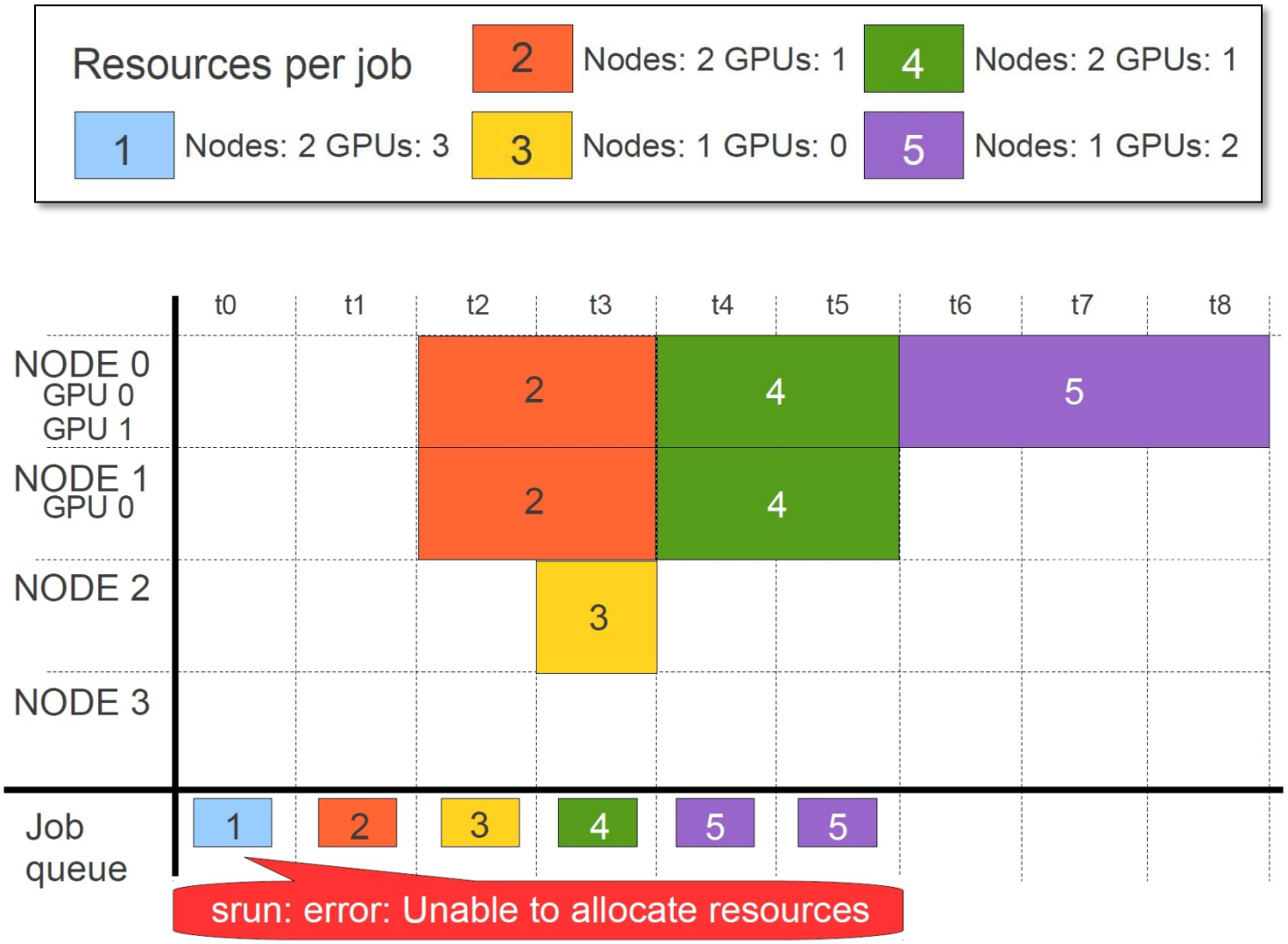
Environment variables are initialized by SLURM and used by the rCUDA client (transparently to the user)

RCUDA_DEVICE_COUNT=4

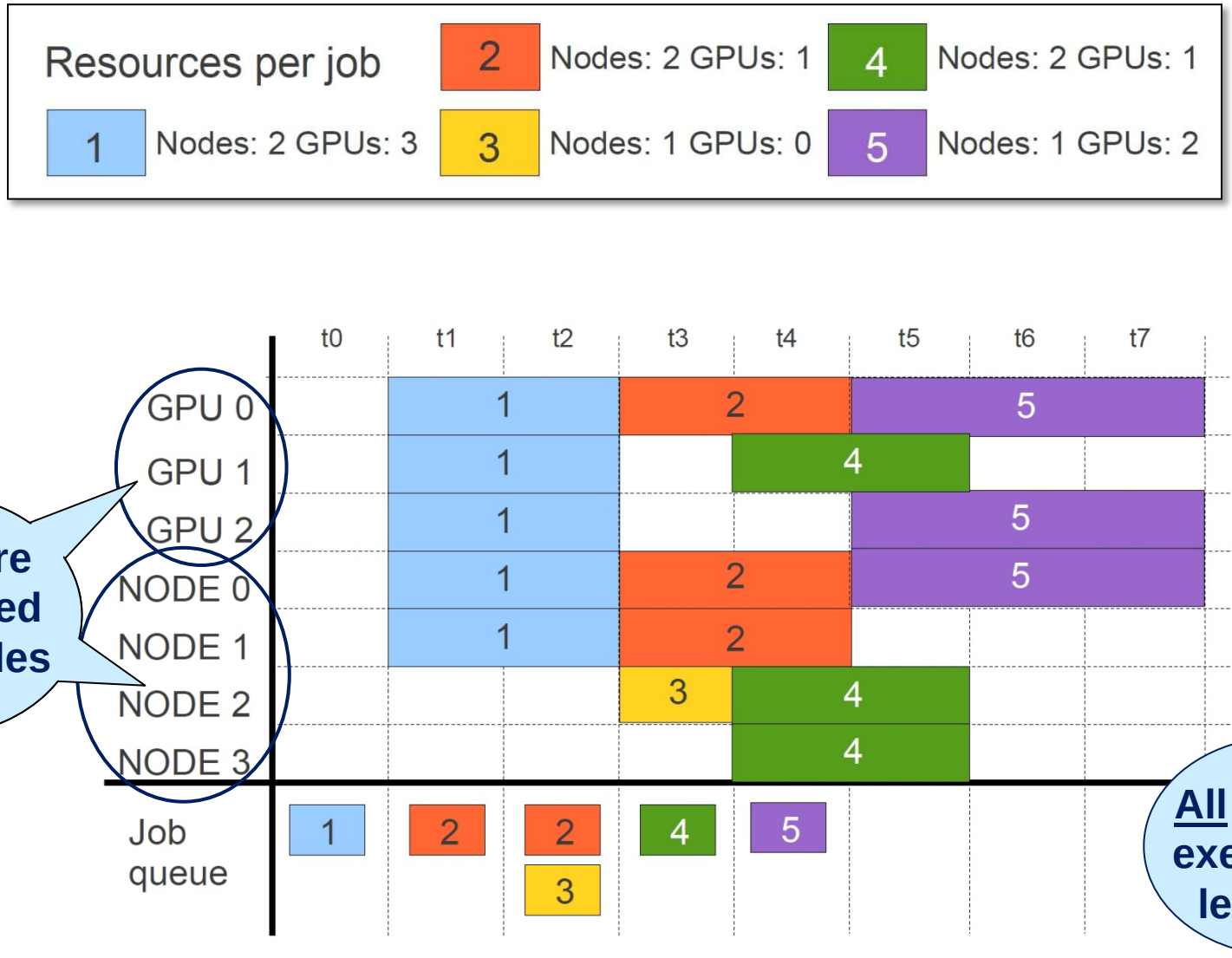
RCUDA_DEVICE_0=rcu16:0
RCUDA_DEVICE_1=rcu16:1
RCUDA_DEVICE_2=rcu16:2
RCUDA_DEVICE_3=rcu16:3

Server name/IP address : GPU

Integrating rCUDA with SLURM



Integrating rCUDA with SLURM

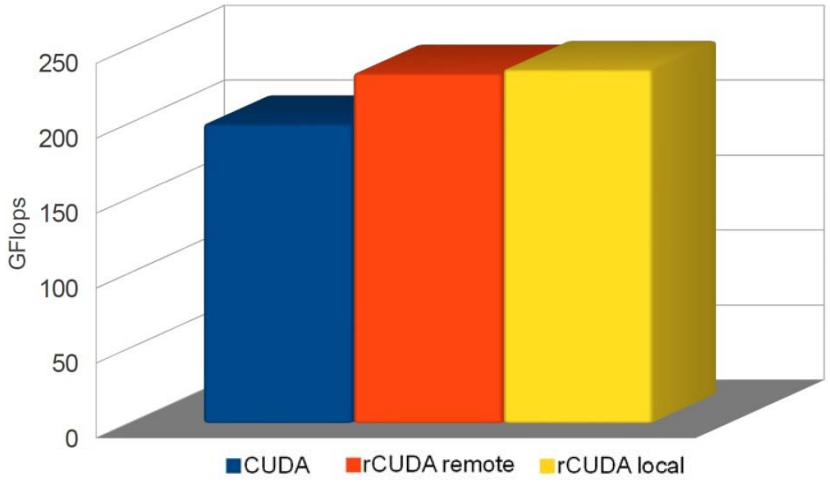


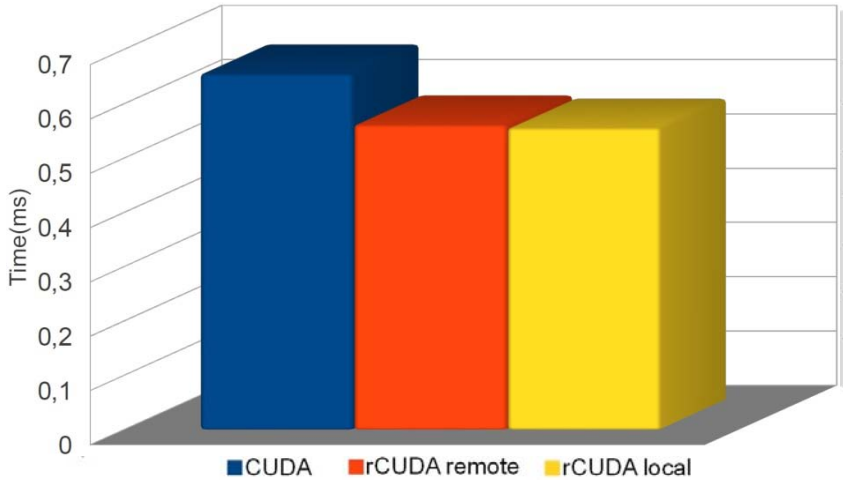
Integrating rCUDA with SLURM

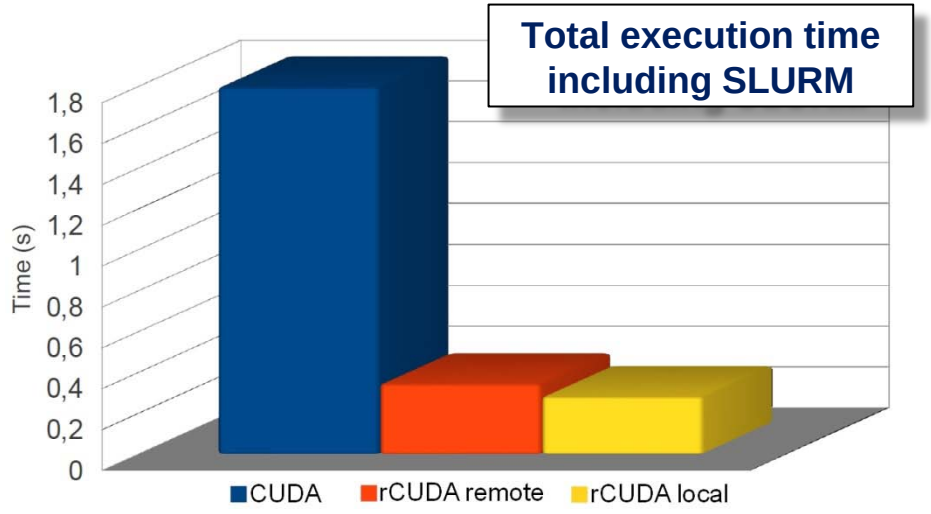
- Test bench for the SLURM experiments:
  - Old “heterogeneous” cluster with 28 nodes:
    - 1 node without GPU, with 2 AMD Opteron 1.4GHz, 6GB RAM
    - 23 nodes without GPU with 2 AMD Opteron 1.4GHz, 2GB RAM
    - 1 node without GPU, QuadCore i7 3.5GHz, 8GB de RAM
    - 1 node with GeForce GTX 670 2GB, QuadCore i7 3GHz, 8GB RAM
    - 1 node with GeForce GTX 670 2GB, Core2Duo 2.4GHz, 2GB RAM
    - 1 node with 2 GeForce GTX 590 3GB, Quad Core i7 3.5GHz, 8GB RAM
    - 1Gbps Ethernet
    - Scientific Linux release 6.1 and also Open Suse 11.2 (dual boot)

Integrating rCUDA with SLURM

- matrixMul from NVIDIA's SDK
  - matrixA 320x320
  - matrixB 640x320



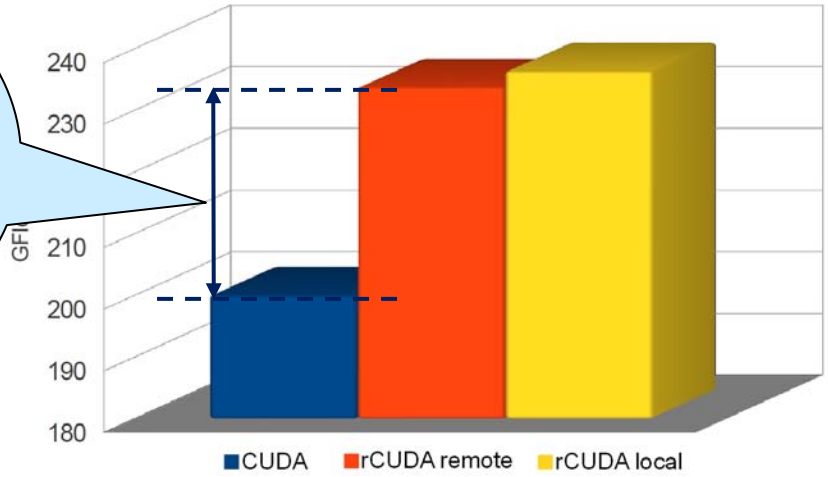


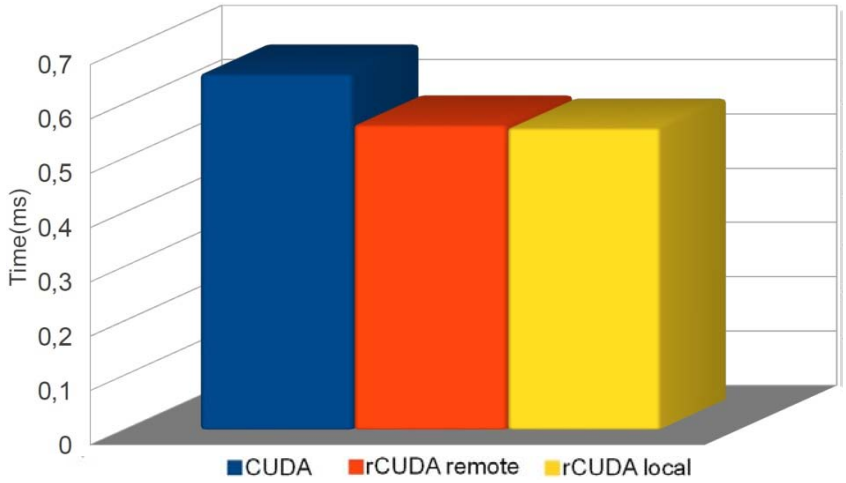


Integrating rCUDA with SLURM

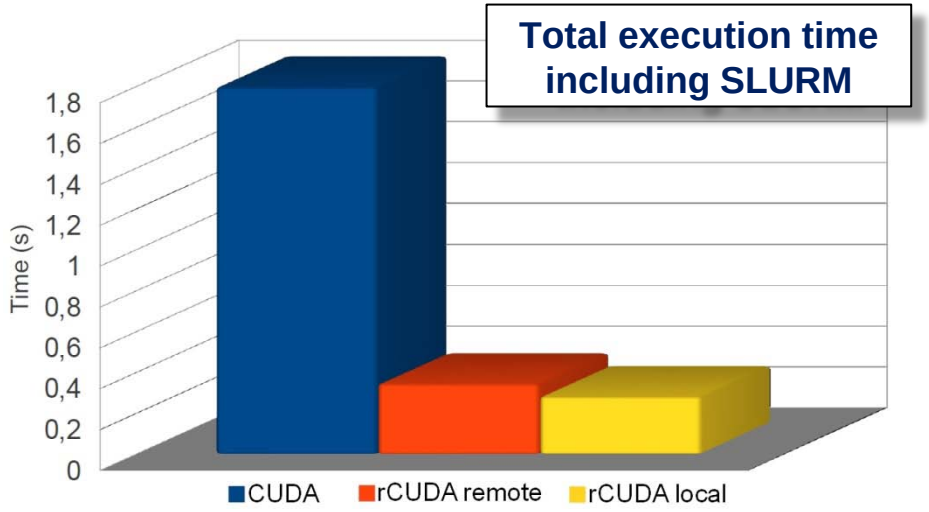
- matrixMul from NVIDIA's SDK

The higher performance of rCUDA is due to a pre-initialized CUDA environment in the rCUDA server





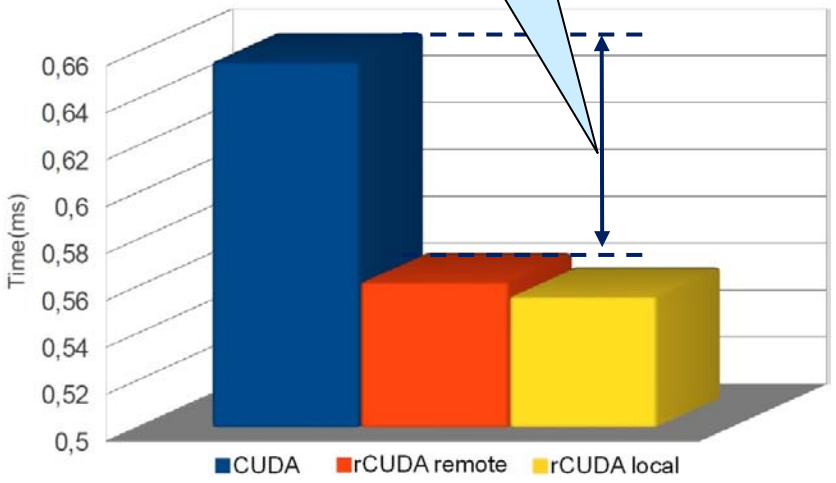
Total execution time including SLURM

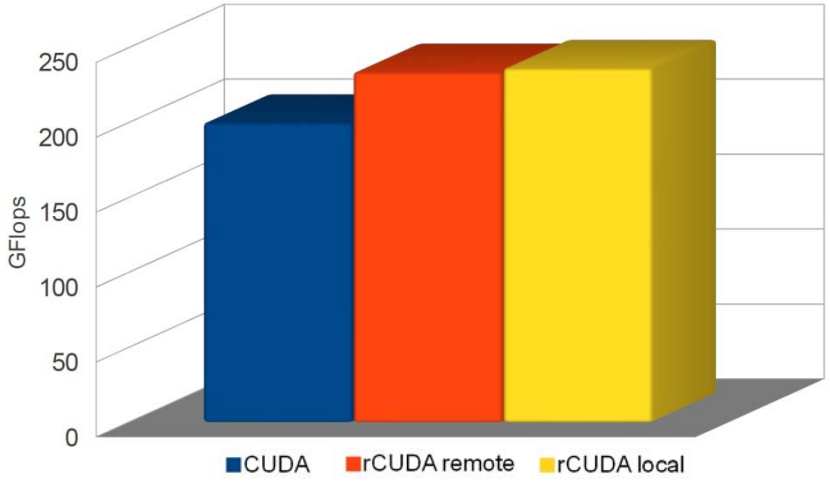


Integrating rCUDA with SLURM

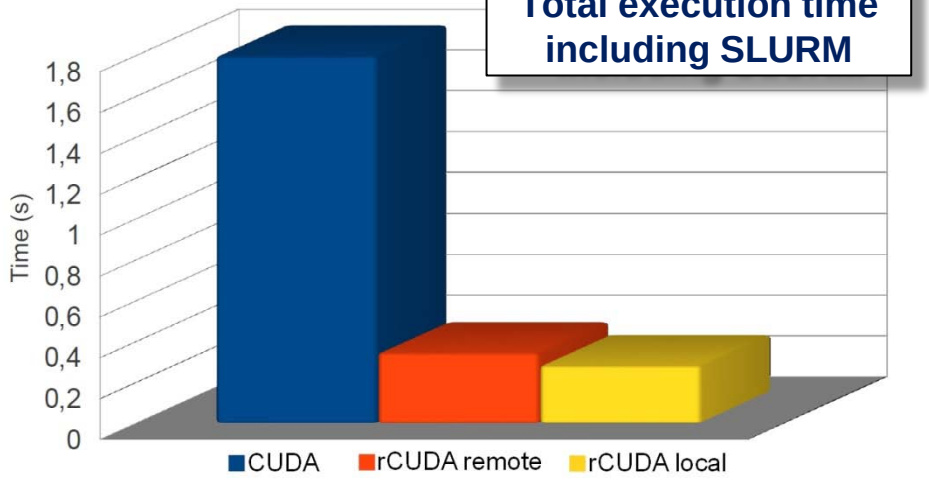
- matrixMul from NVIDIA's SDK

The time for initializing the CUDA environment is about 0.9 seconds



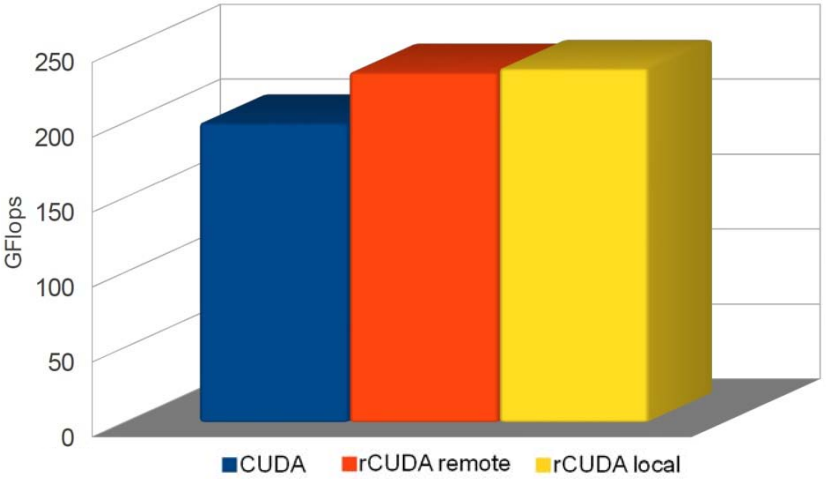


Total execution time including SLURM

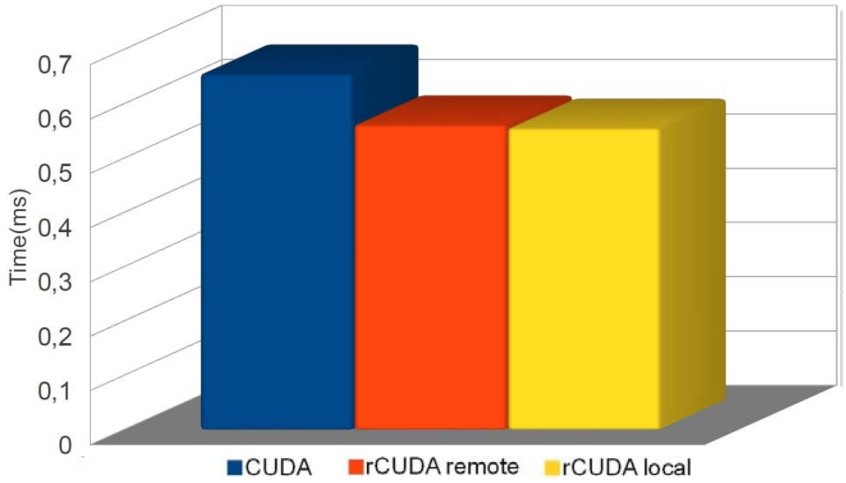


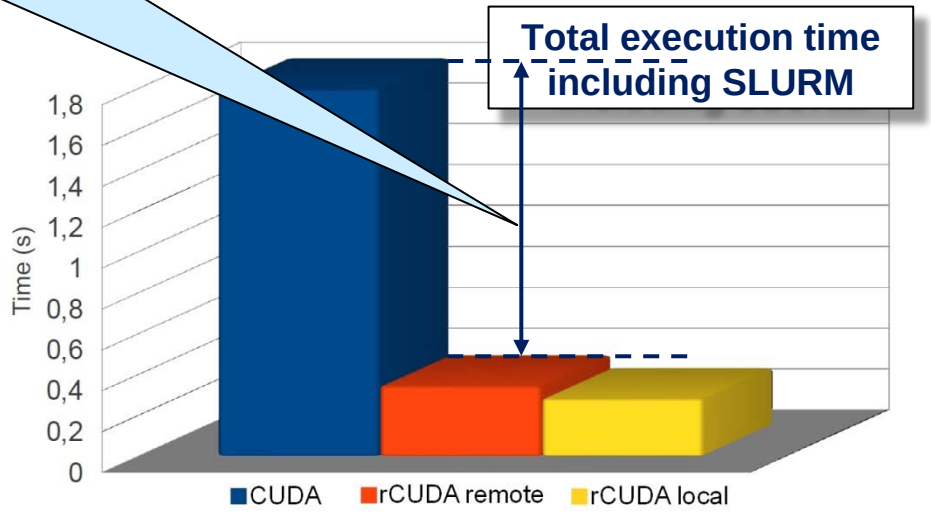
Integrating rCUDA with SLURM

- matrixMul from NVIDIA's SDK



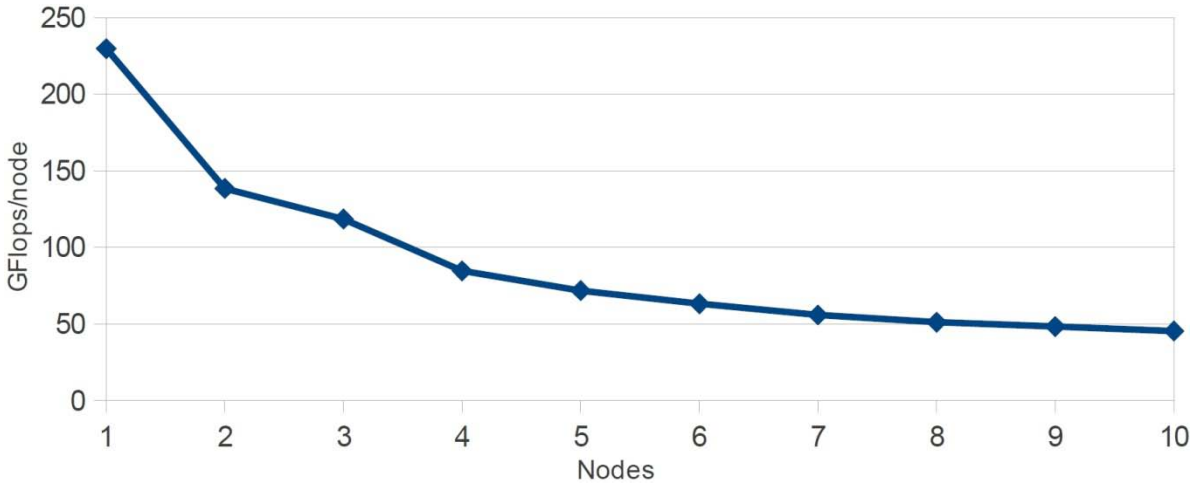
Scheduling the use of remote GPUs takes less time than finding a local available GPU

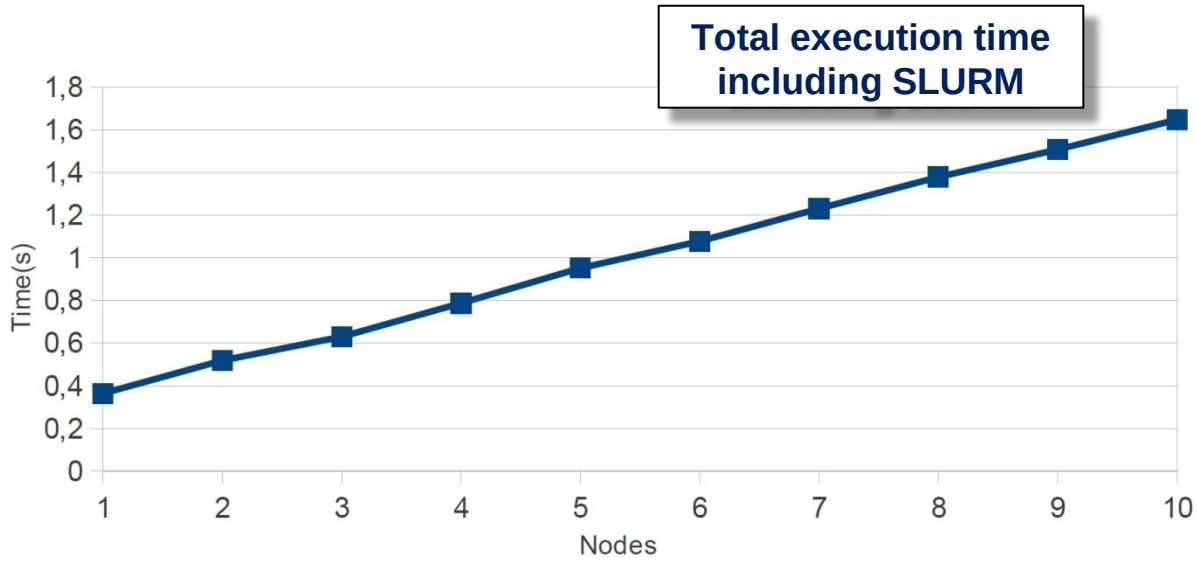




Integrating rCUDA with SLURM

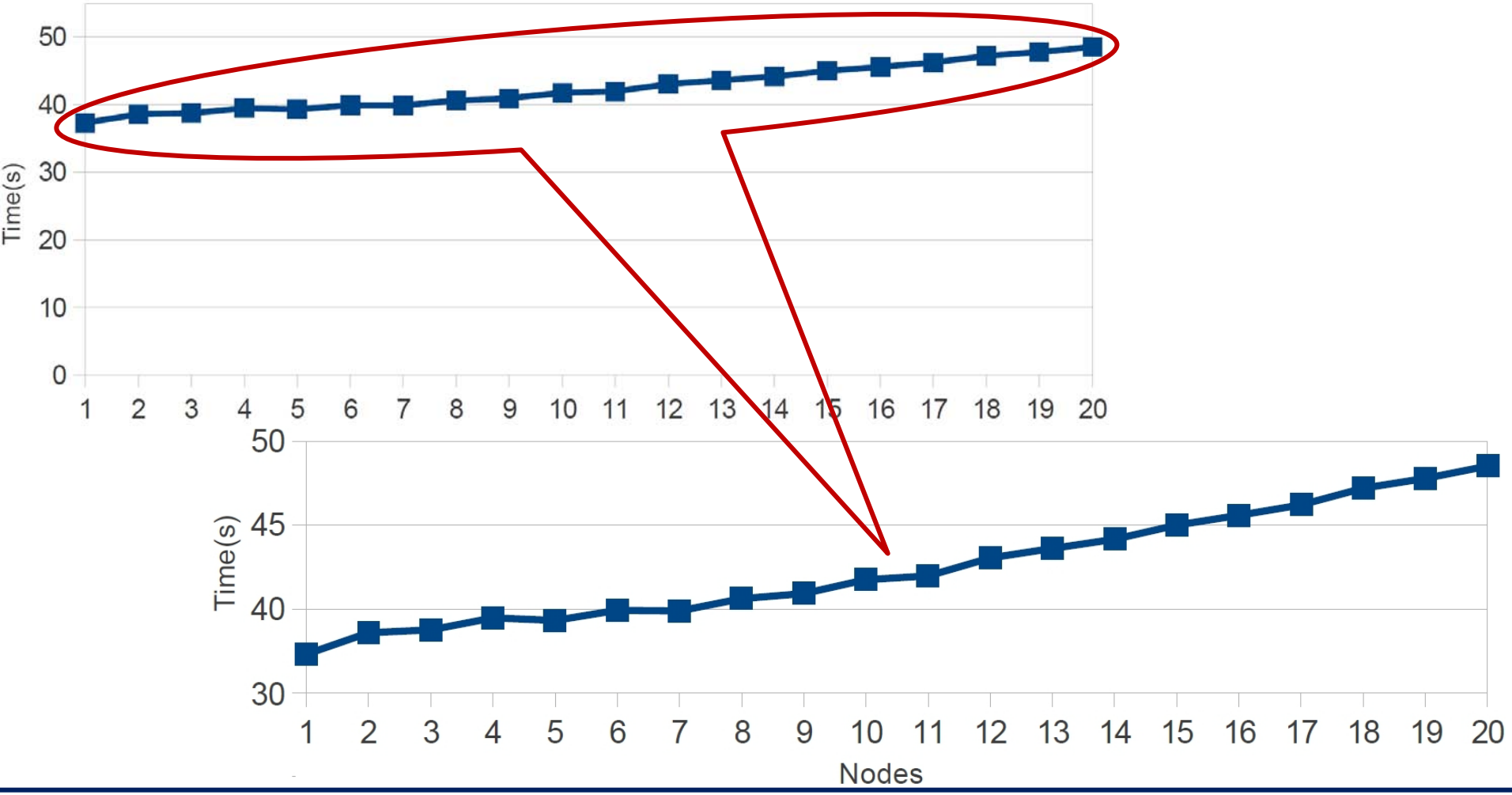
- Sharing remote GPUs among processes (matrixMul)



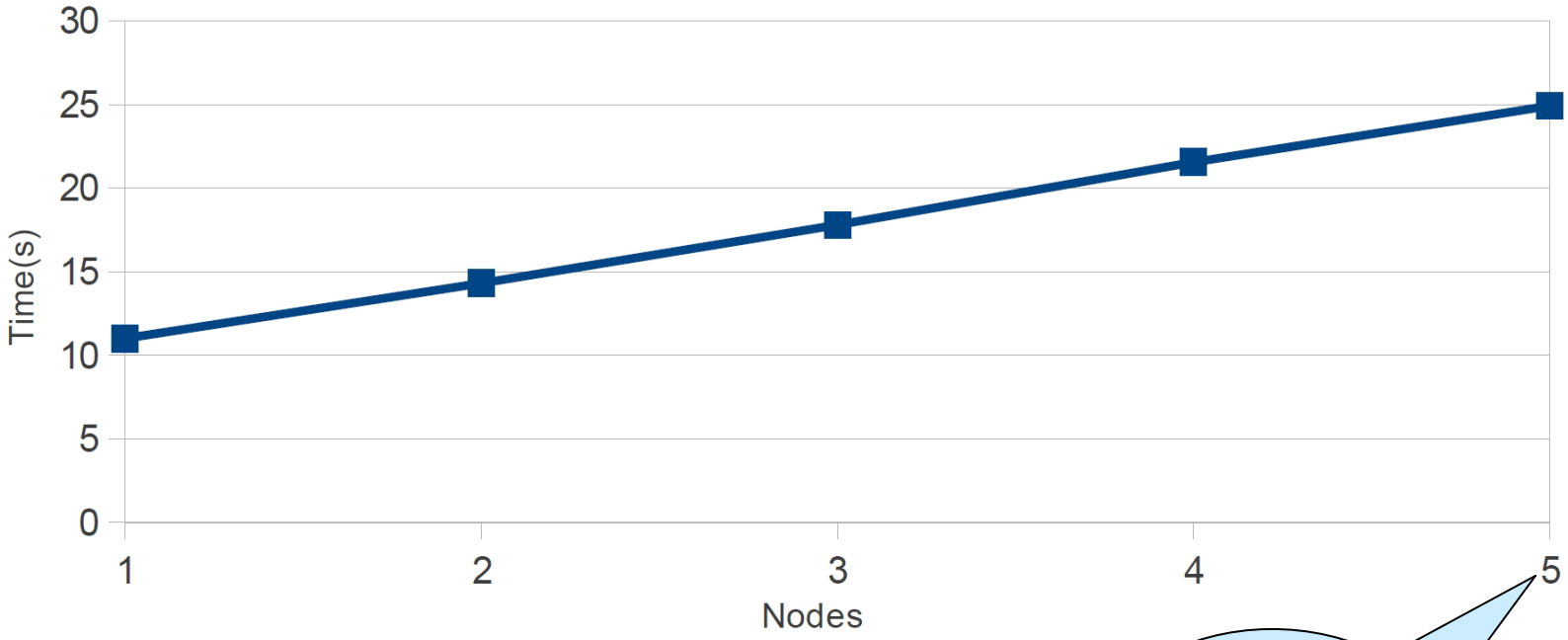


Integrating rCUDA with SLURM

- Sharing remote GPUs among processes
  - sortingNetworks from NVIDIA's SDK



- Sharing remote GPUs among processes (CUDASW++)



The GPU memory gets full with 5 concurrent executions

Outline

- Current GPU computing facilities
- How GPU virtualization adds value to your cluster
- The rCUDA framework: basics and performance
- Integrating rCUDA with SLURM
- **rCUDA and low-power processors**

rCUDA and low-power processors

- There is a clear trend to improve the performance-power ratio in HPC facilities:
  - By leveraging accelerators (Tesla K20 by NVIDIA, FirePro by AMD, Xeon Phi by Intel, …)
  - More recently, by using low-power processors (Intel Atom, ARM, …)
- rCUDA allows to attach a “pool of accelerators” to a computing facility:
  - Less accelerators than nodes → accelerators shared among nodes
  - Performance-power ratio probably improved further
- How interesting is a heterogeneous platform leveraging powerful processors, low-power ones, and remote GPUs?
  - Which is the best configuration?
  - Is energy effectively saved?

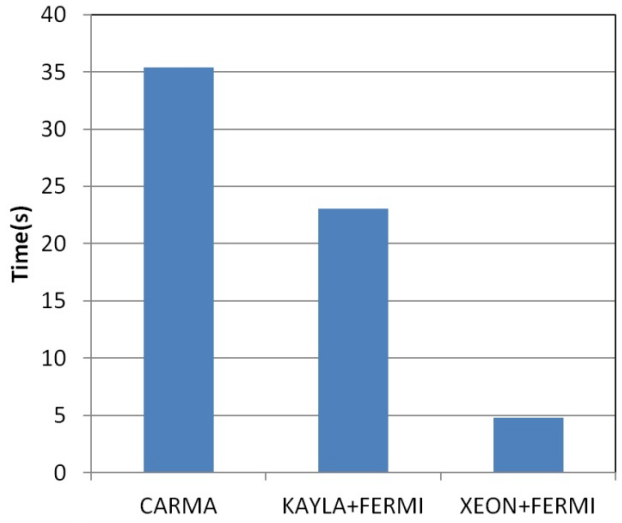
rCUDA and low-power processors

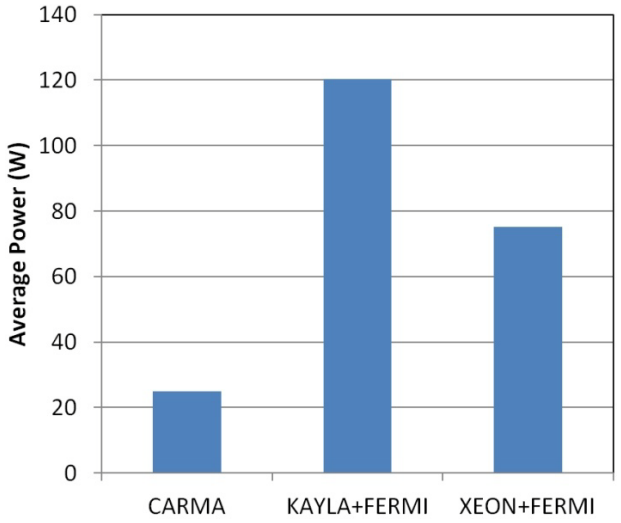
- The **computing platforms** analyzed in this study are:
  - **KAYLA**: NVIDIA Tegra 3 ARM Cortex A9 quad-core CPU (1.4 GHz), 2GB DDR3 RAM and Intel 82574L Gigabit Ethernet controller
  - **ATOM**: Intel Atom quad-core CPU s1260 (2.0 GHz), 8GB DDR3 RAM and Intel I350 Gigabit Ethernet controller. **No PCIe connector for a GPU**
  - **XEON**: Intel Xeon X3440 quad-core CPU (2.4GHz), 8GB DDR3 RAM and 82574L Gigabit Ethernet controller
- The **accelerators** analyzed are:
  - **CARMA**: NVIDIA Quadro 1000M GPU (96 cores) with 2GB DDR5 RAM. The rest of the system is the same as for KAYLA
  - **FERMI**: NVIDIA GeForce GTX480 “Fermi” GPU (448 cores) with 1,280 MB DDR3/GDDR5 RAM

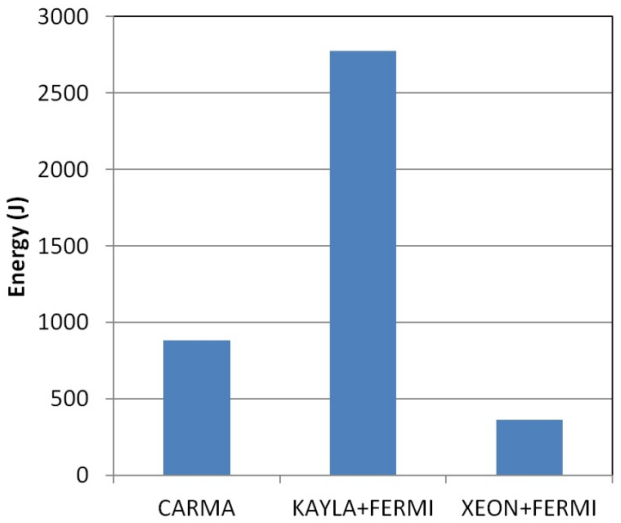
CARMA platform

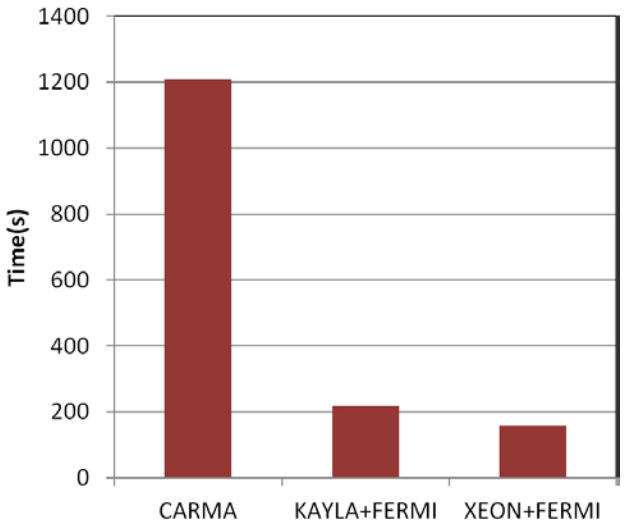
rCUDA and low-power processors

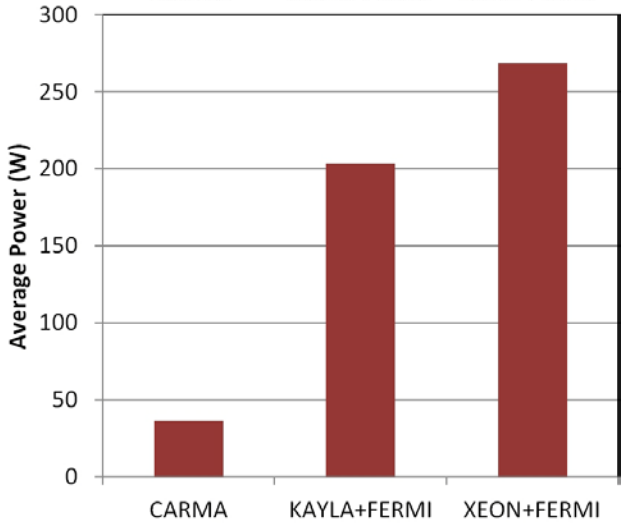
- 1st analysis: using **local GPUs**; CUDASW++ (top) LAMMPS (bottom)

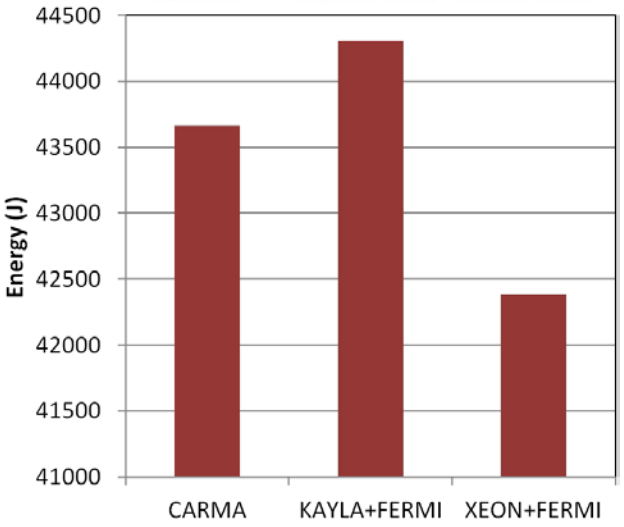






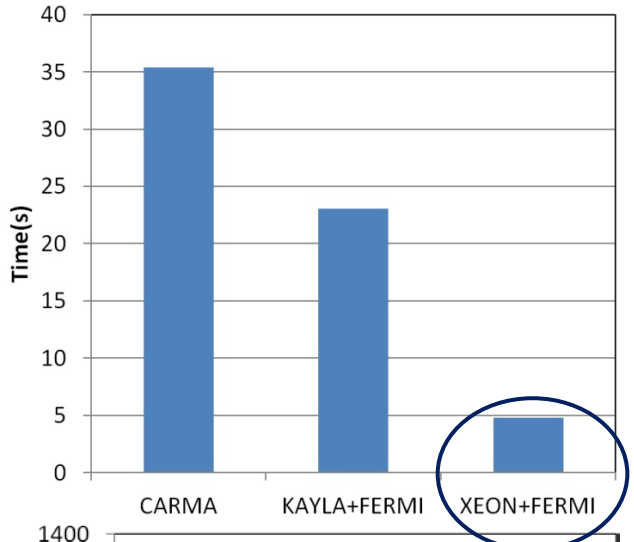


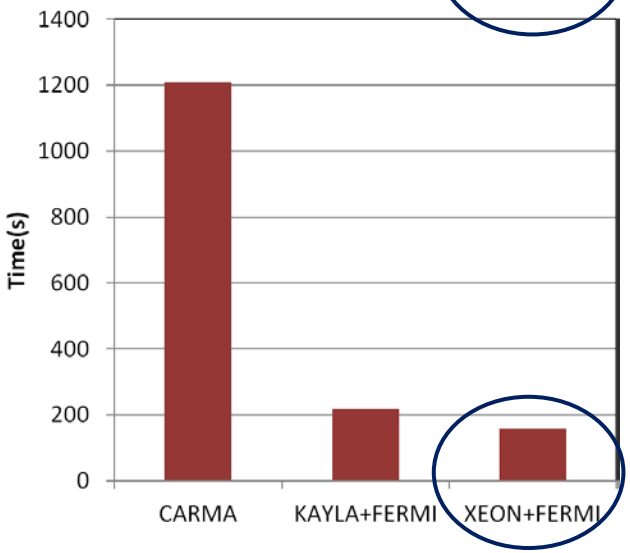




rCUDA and low-power processors

- 1st analysis: using **local GPUs**; CUDASW++ (top) LAMMPS (bottom)

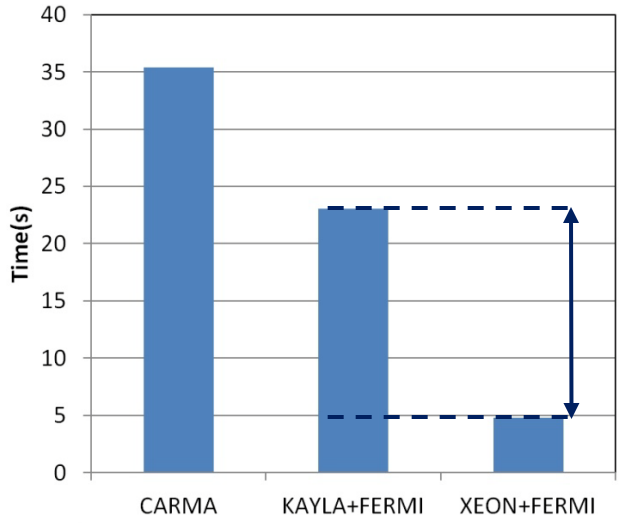


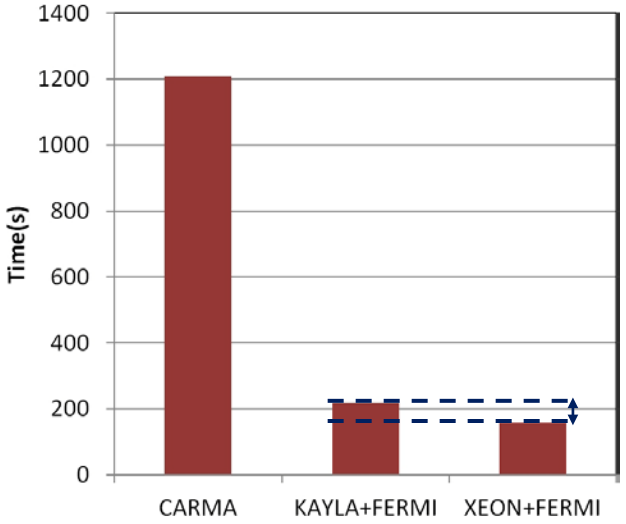


- The XEON+FERMI combination achieves the best performance

rCUDA and low-power processors

- 1st analysis: using **local GPUs**; CUDASW++ (top) LAMMPS (bottom)

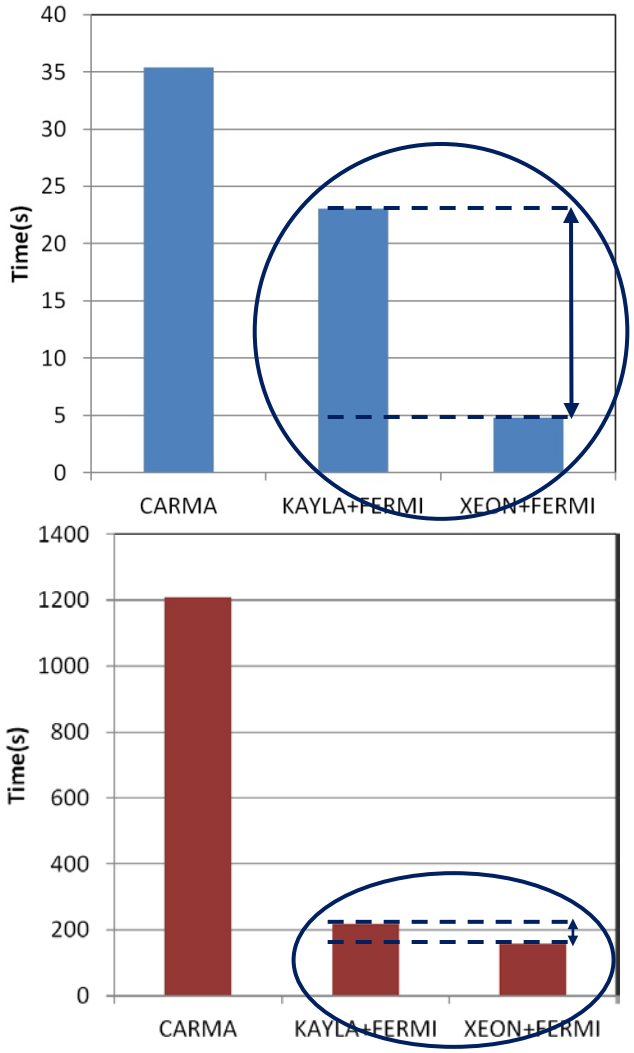




- The XEON+FERMI combination achieves the best performance
- LAMMPS makes a more intensive use of the GPU than CUDASW++

rCUDA and low-power processors

- 1st analysis: using **local GPUs**; CUDASW++ (top) LAMMPS (bottom)



- The XEON+FERMI combination achieves the best performance
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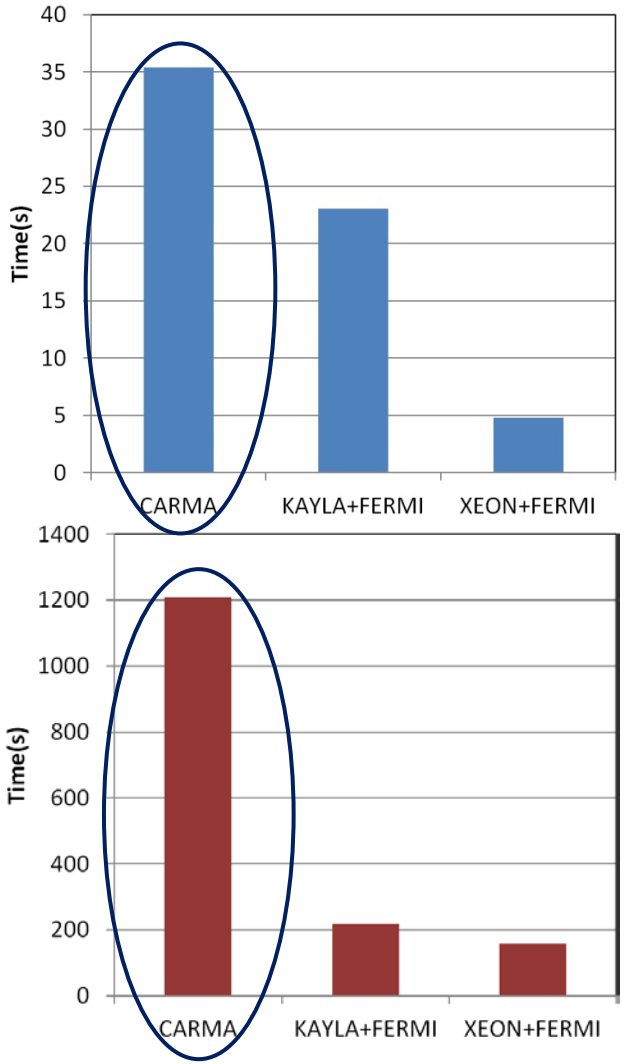
- The lower performance of the PCIe bus in Kayla reduces performance

rCUDA and low-power processors

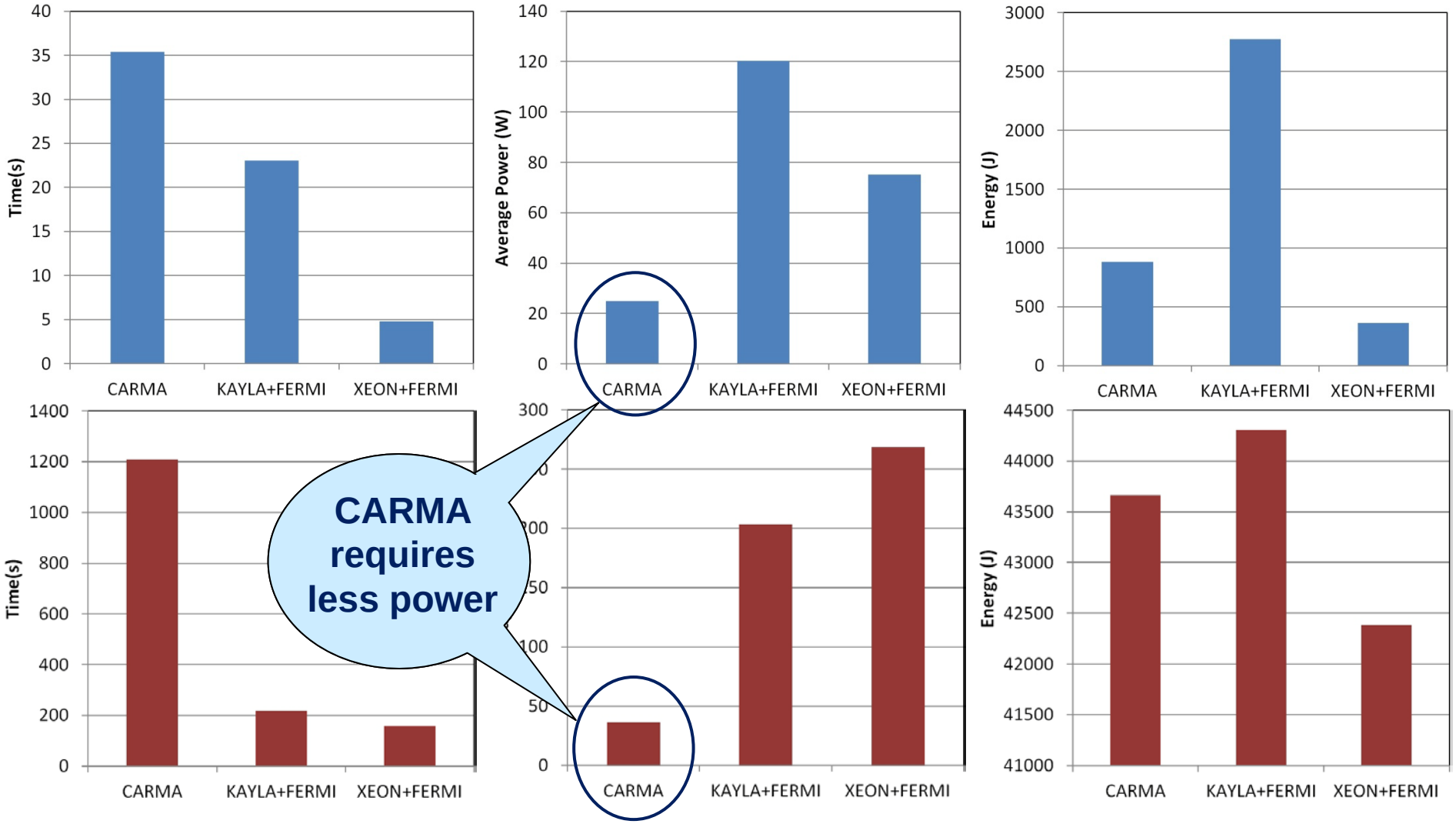
- 1st analysis: using **local GPUs**; CUDASW++ (top) LAMMPS (bottom)



- The XEON+FERMI combination achieves the best performance
- LAMMPS makes a more intensive use of the GPU than CUDASW++
- The lower performance of the PCIe bus in Kayla reduces performance
- The 96 cores of CARMA provide a noticeably lower performance than a more powerful GPU

rCUDA and low-power processors

- 1st analysis: using **local GPUs**; CUDASW++ (top) LAMMPS (bottom)



rCUDA and low-power processors

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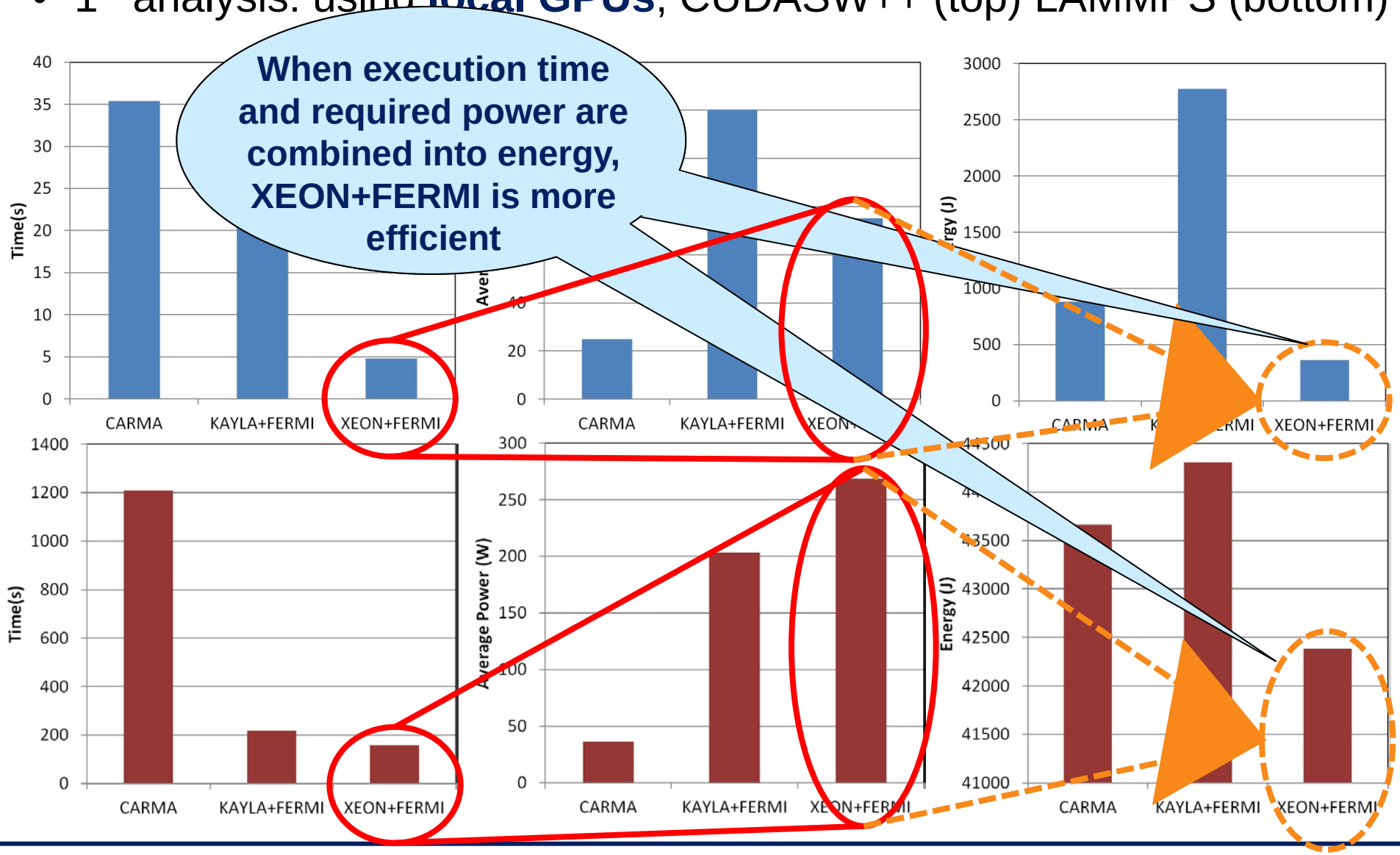

rCUDA and low-power processors

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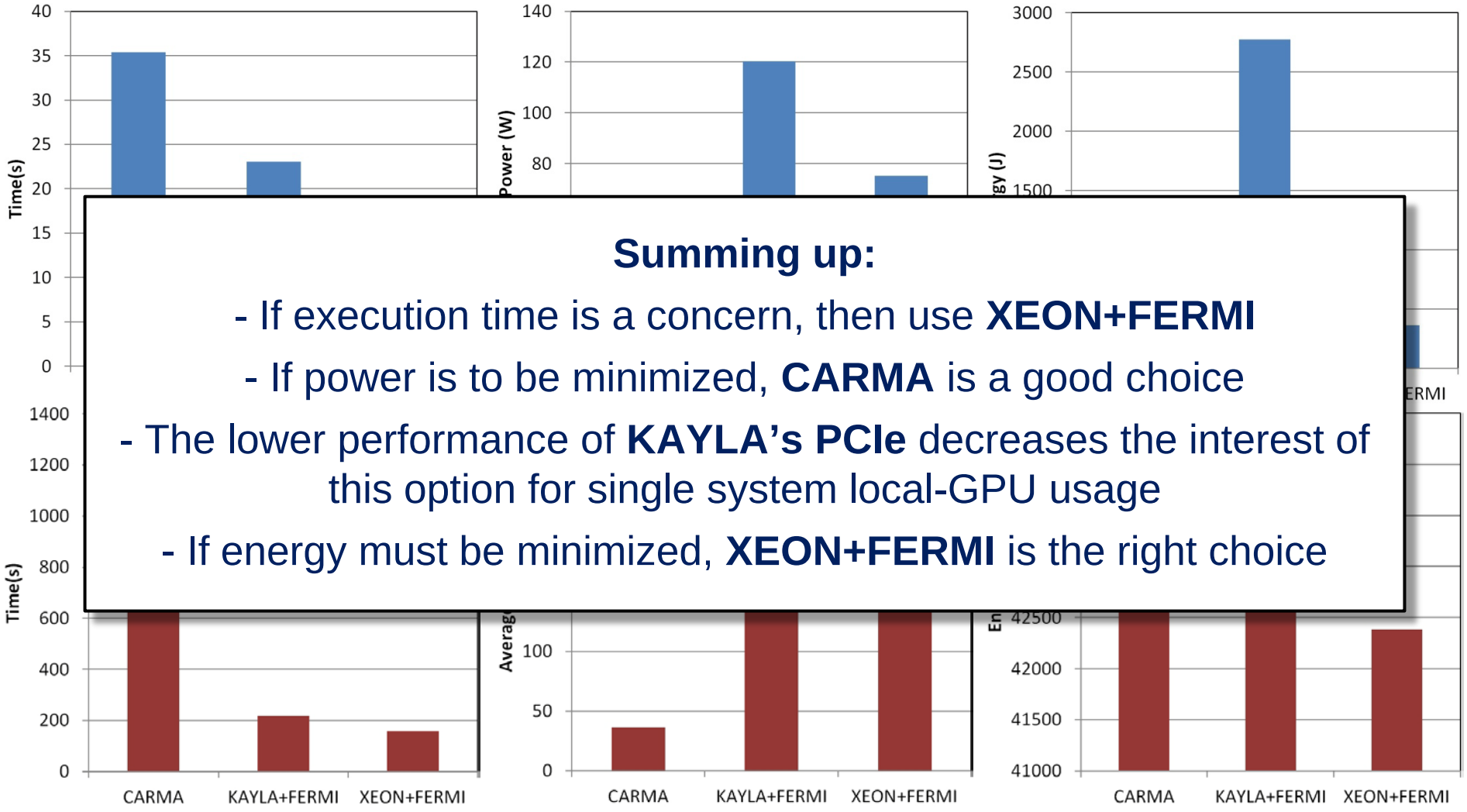


Summing up:

- If execution time is a concern, then use **XEON+FERMI**
- If power is to be minimized, **CARMA** is a good choice
- The lower performance of **KAYLA's PCIe** decreases the interest of this option for single system local-GPU usage
- If energy must be minimized, **XEON+FERMI** is the right choice

rCUDA and low-power processors

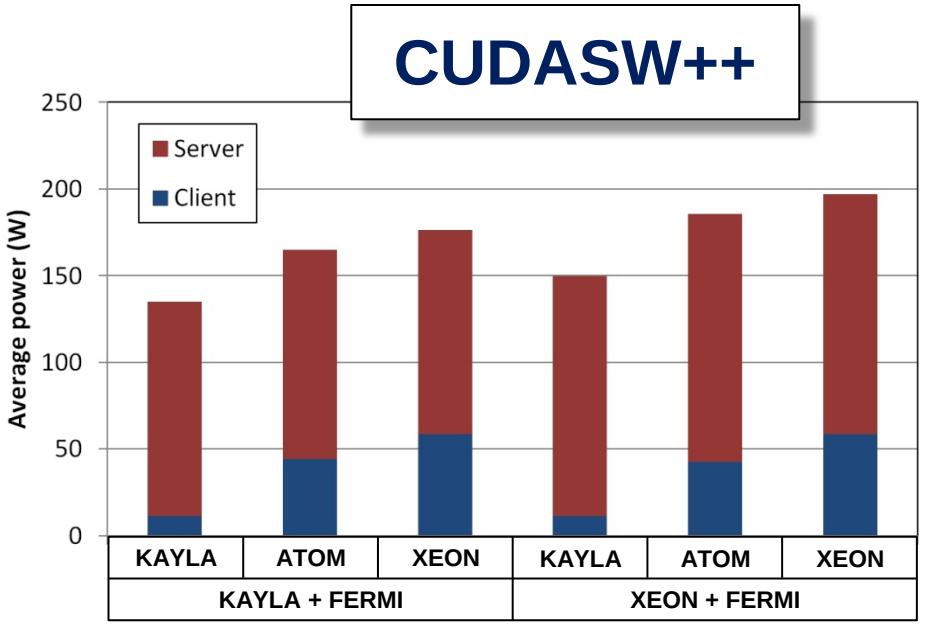
- 2nd analysis: use of **remote GPUs**
  - The use of the CUADRO GPU within the CARMA system is discarded as rCUDA server due to its poor performance. **Only the FERMI GPU is considered**
  - Six different combinations of rCUDA clients and servers are feasible:

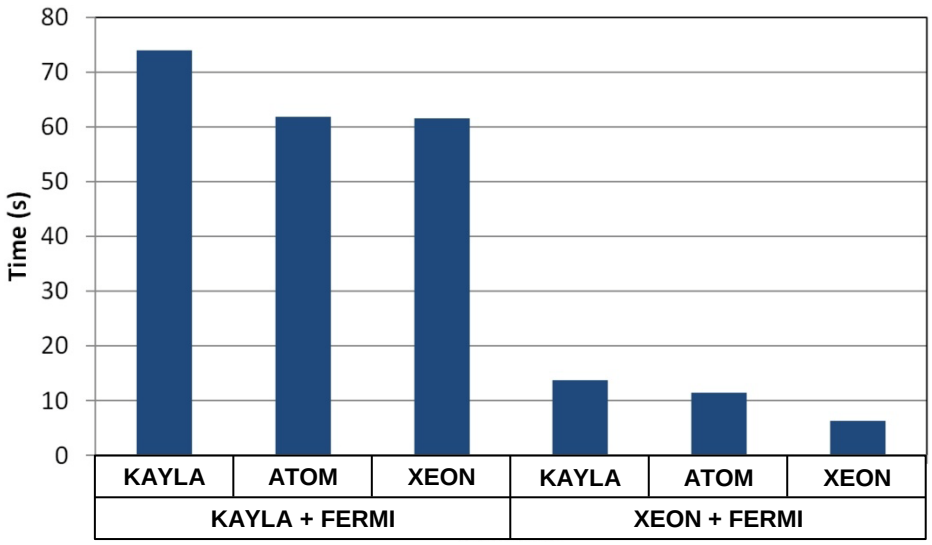
Combination	Client	Server
1	KAYLA	KAYLA+FERMI
2	ATOM	KAYLA+FERMI
3	XEON	KAYLA+FERMI
4	KAYLA	XEON+FERMI
5	ATOM	XEON+FERMI
6	XEON	XEON+FERMI

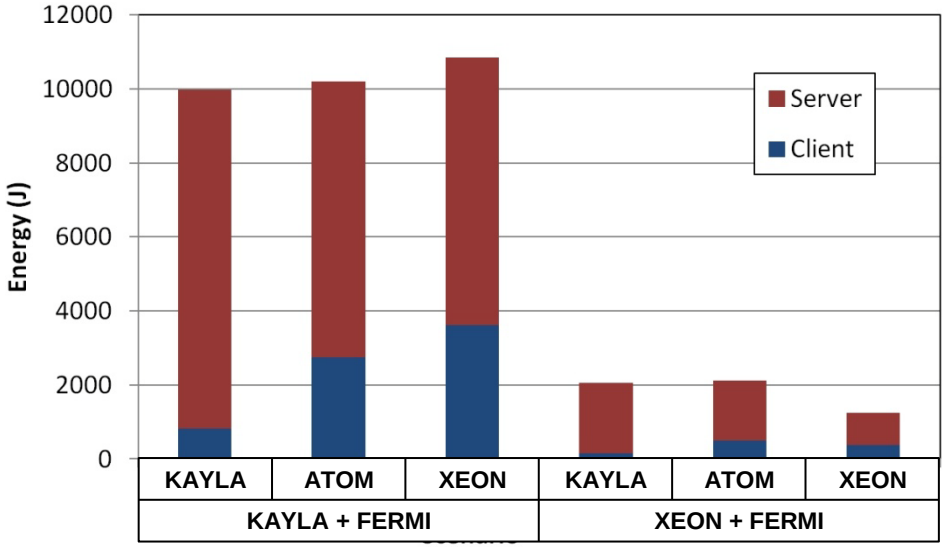
  - Only one client system and one server system are used at each experiment

rCUDA and low-power processors

- 2nd analysis: use of **remote GPUs**



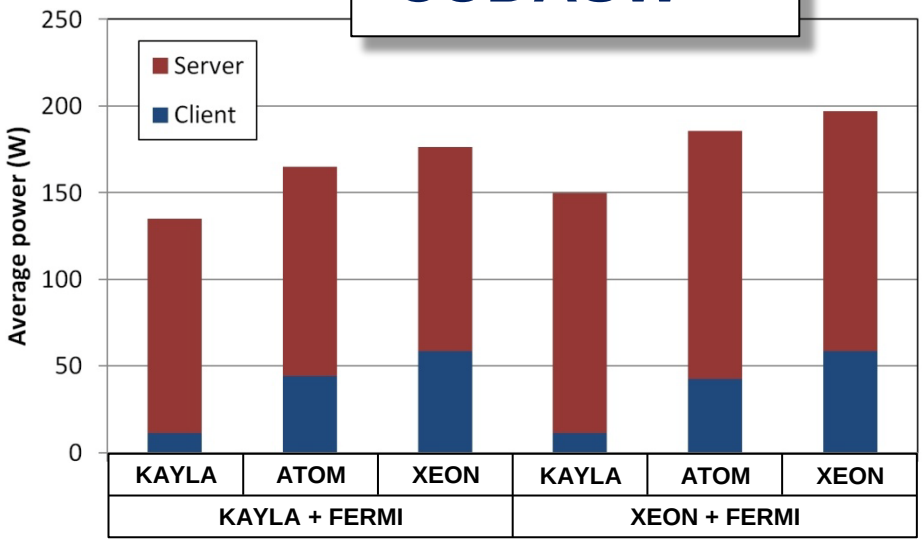




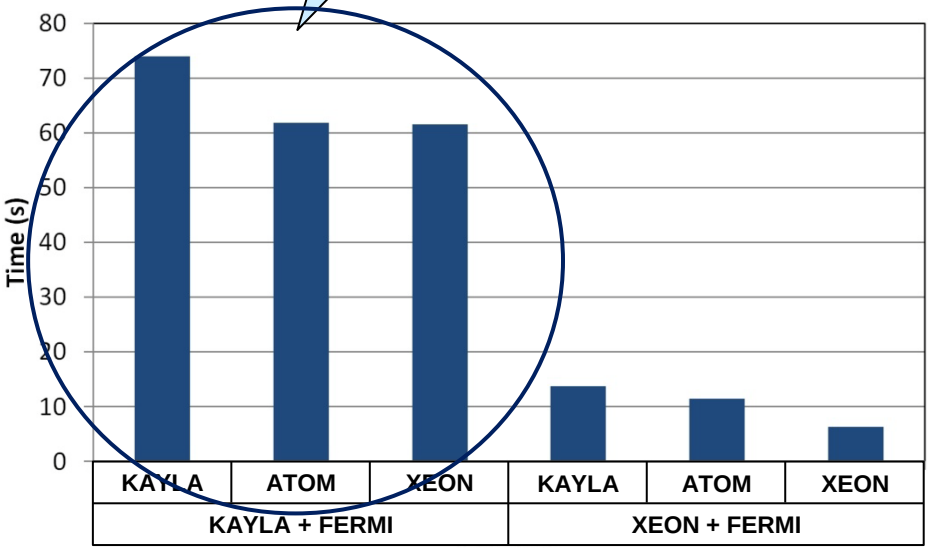
rCUDA and low-power processors

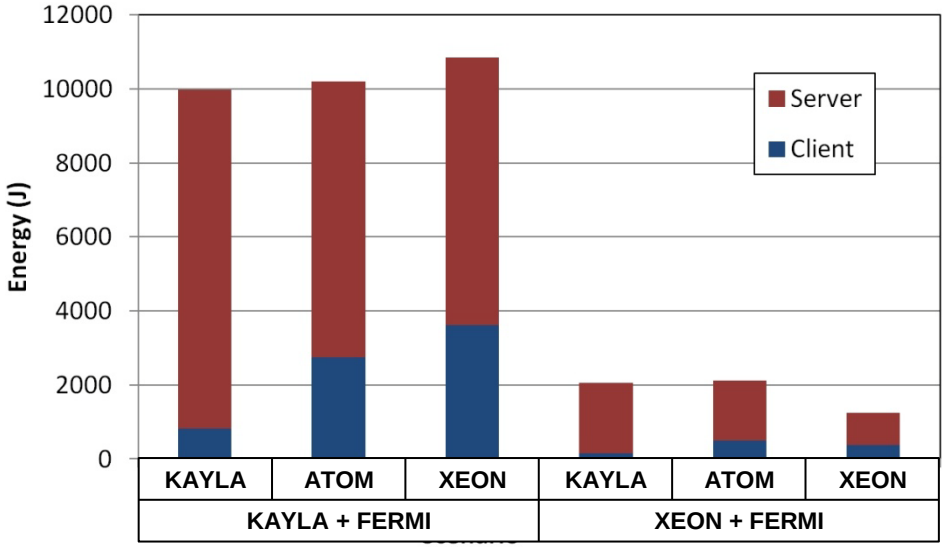
- 2nd analysis: use of **remote GPUs**

CUDASW++



The KAYLA-based server presents much higher execution time

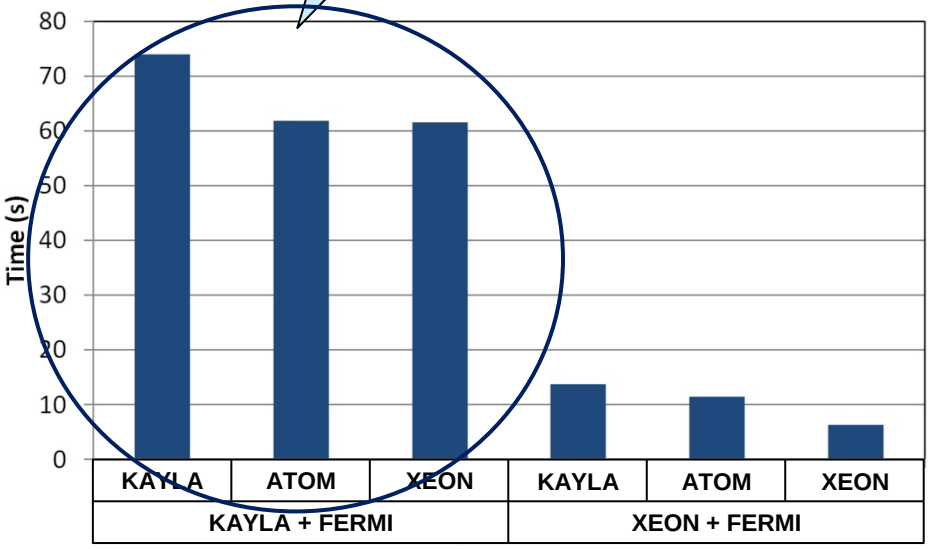




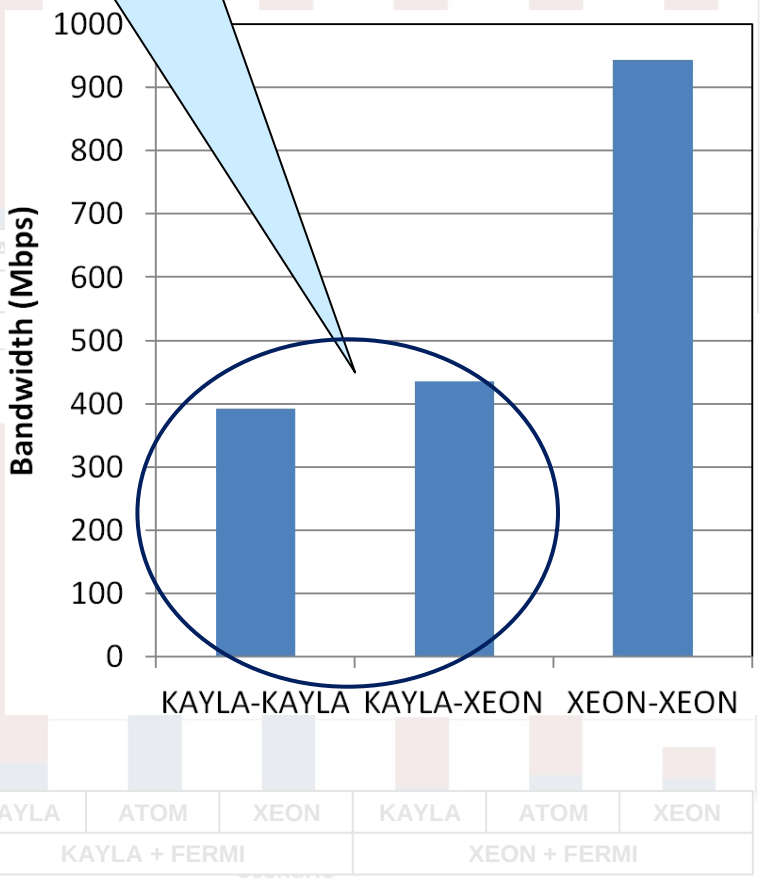
rCUDA and low-power processors

- 2nd analysis: use of **remote GPUs** … **DASW++**

The KAYLA-based server presents much higher execution time



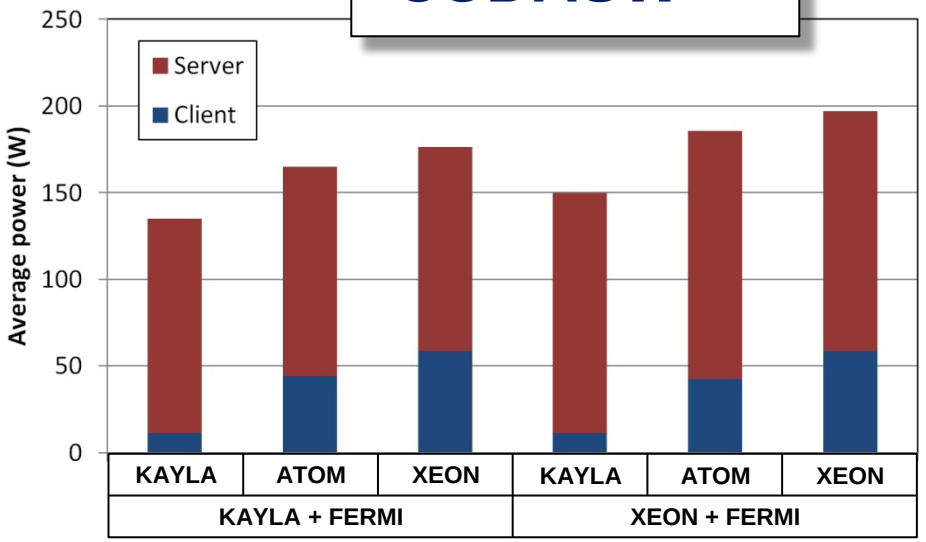
The network interface for KAYLA delivers much less than the expected 1Gbps bandwidth



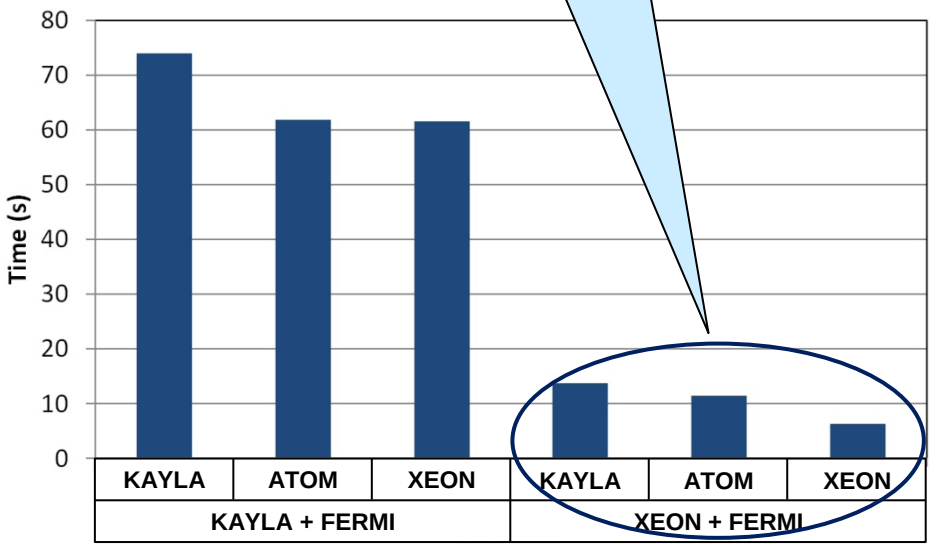
rCUDA and low-power processors

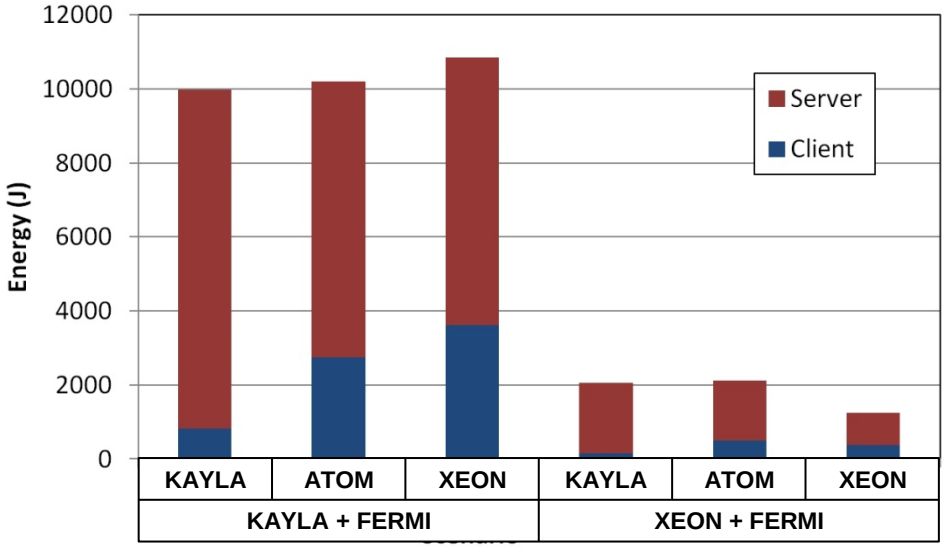
- 2nd analysis: use of **remote GPUs**

CUDASW++



The lower bandwidth of KAYLA (and ATOM) can also be noticed when using the XEON server

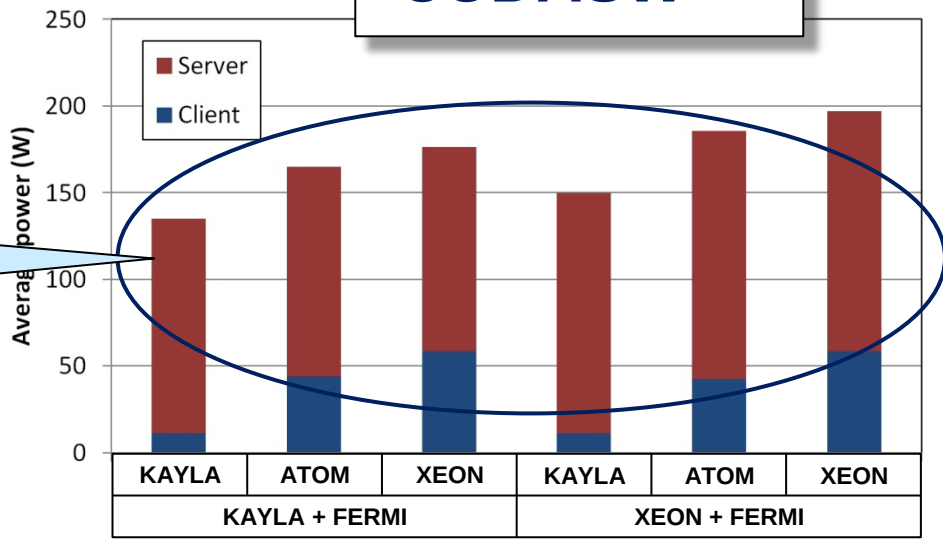


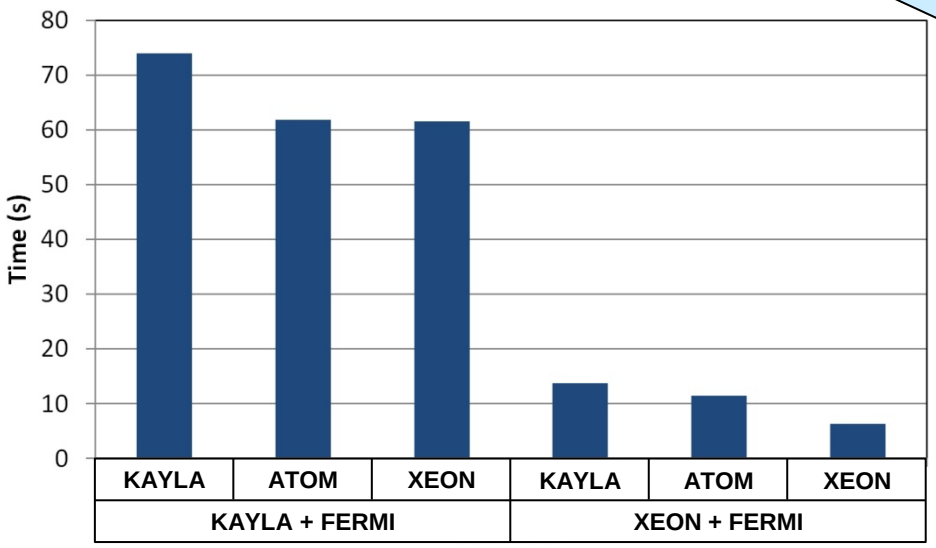


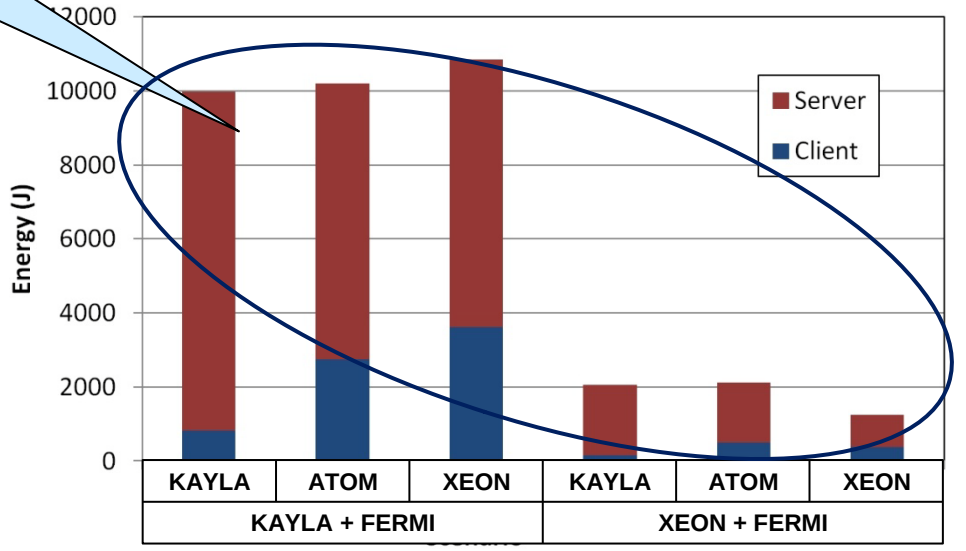
- 2nd analysis: use of **remote GPUs**

CUDASW++

Most of the power and energy is required by the server side, as it hosts the GPU





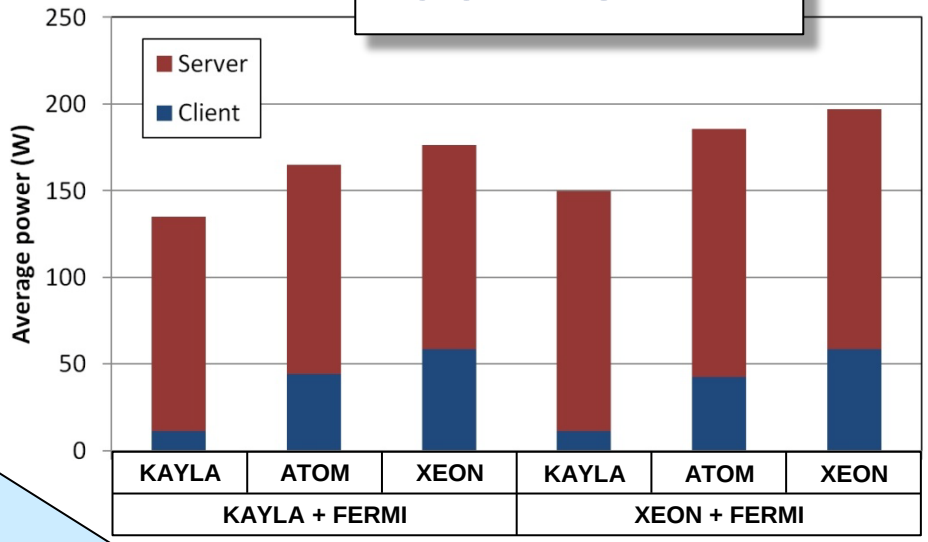


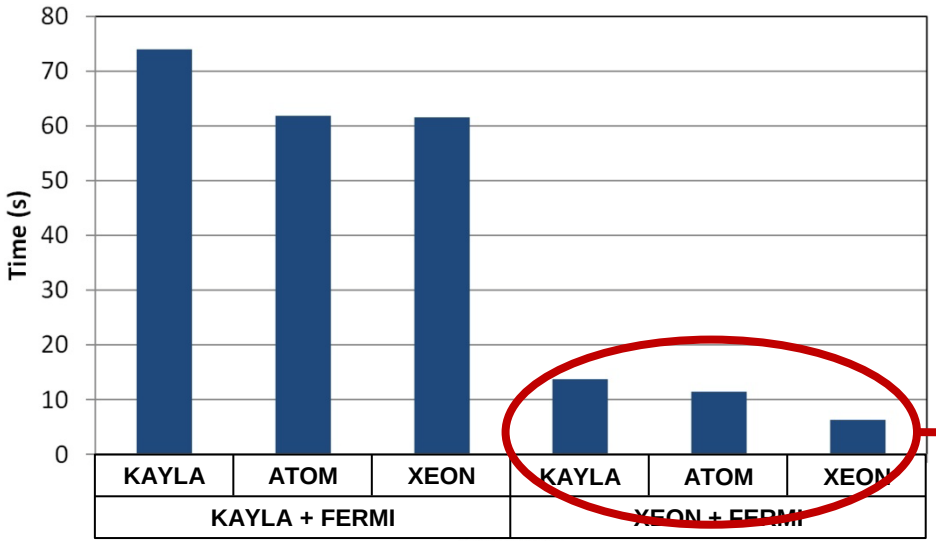
rCUDA and low-power processors

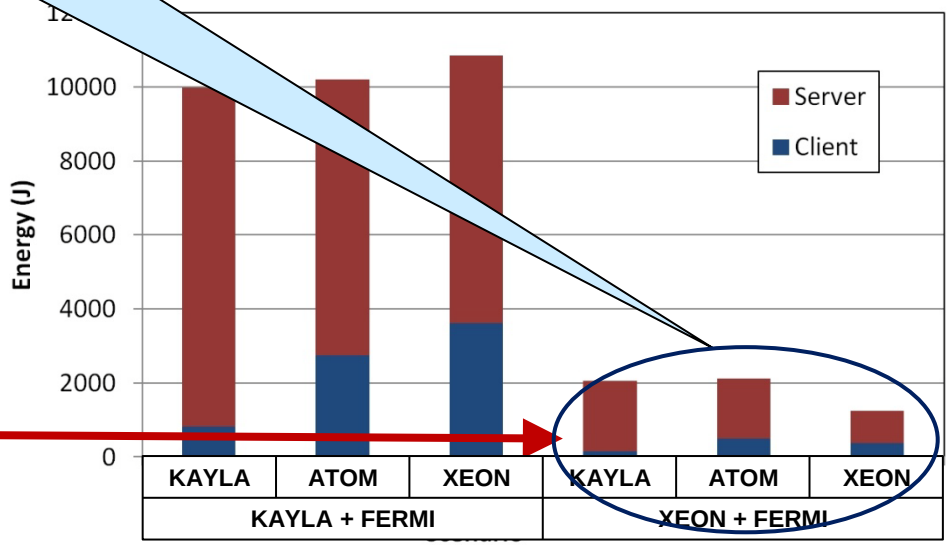
- 2nd analysis: use of **remote GPUs**

CUDASW++

The much shorter execution time of XEON-based servers render more energy-efficient systems



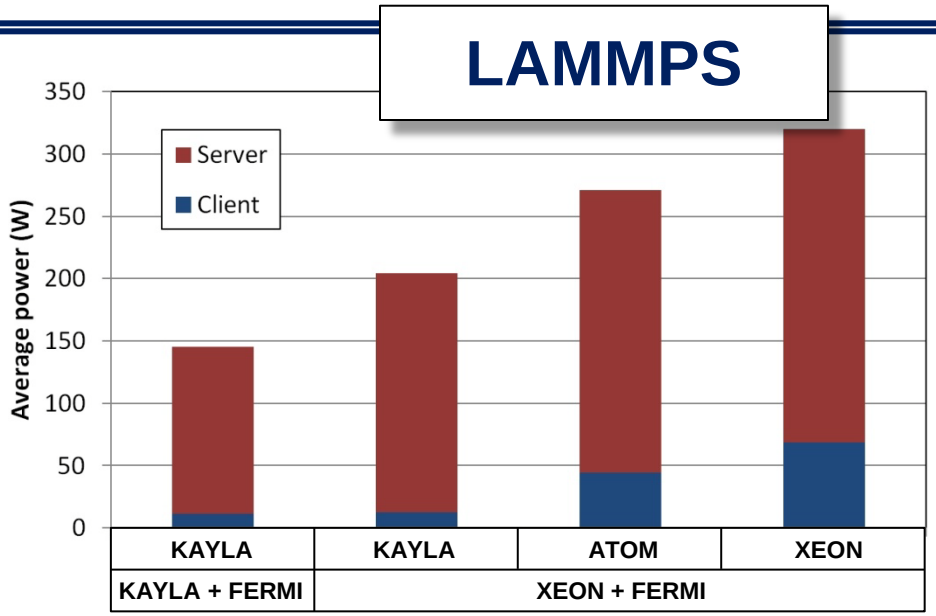


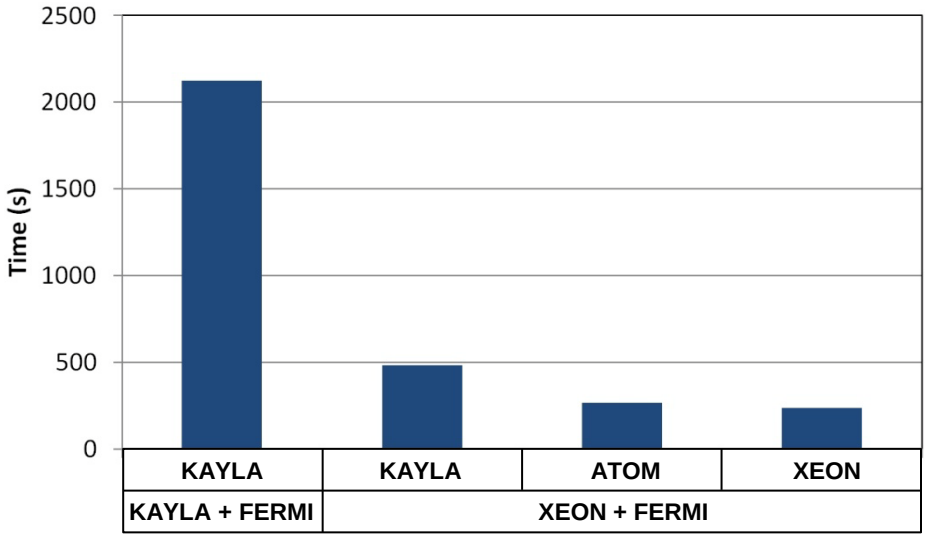


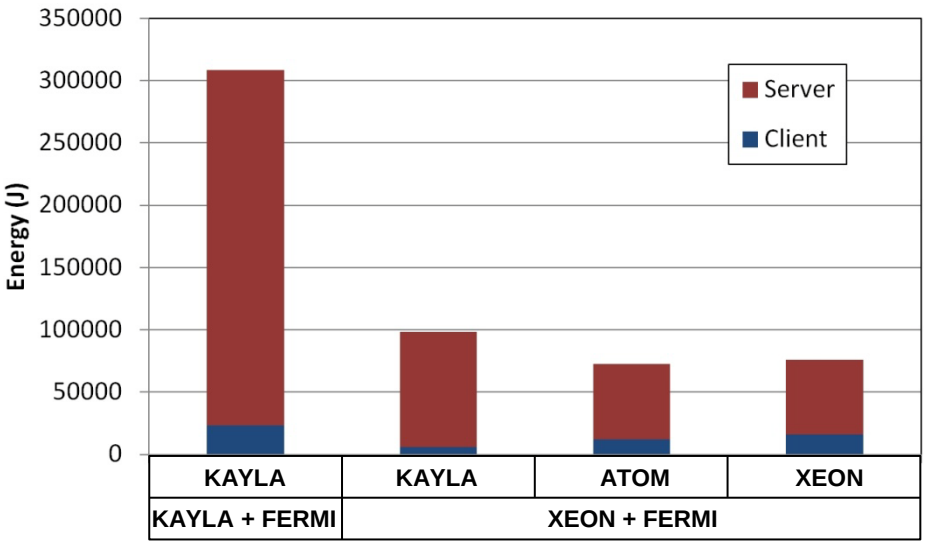
rCUDA and low-power processors

- 2nd analysis: use of **remote GPUs**

Combination	Client	Server
1	KAYLA	KAYLA+FERMI
2	KAYLA	XEON+FERMI
3	ATOM	XEON+FERMI
4	XEON	XEON+FERMI



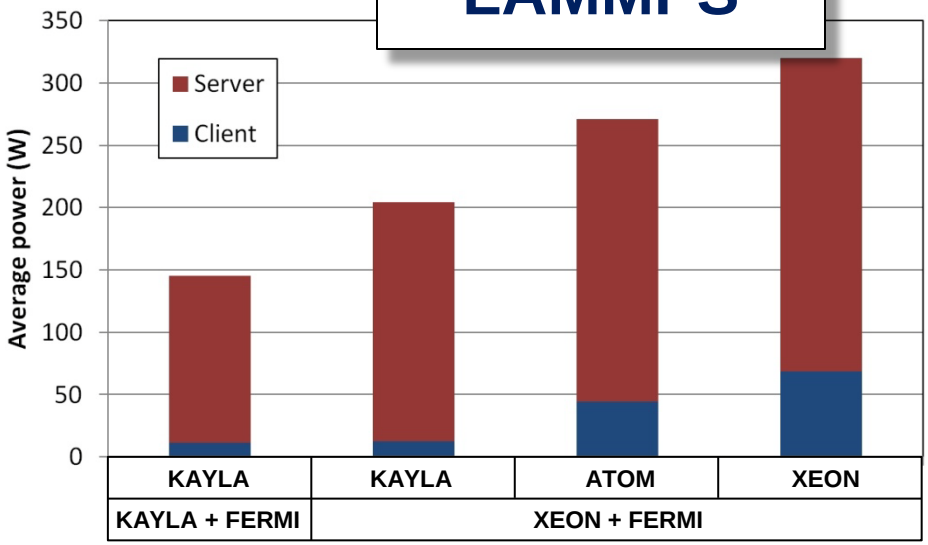




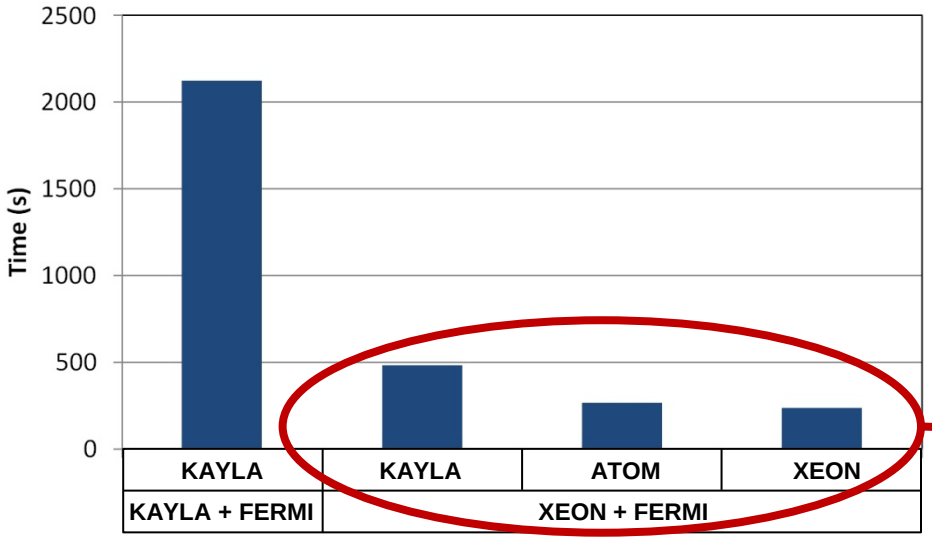
rCUDA and low-power processors

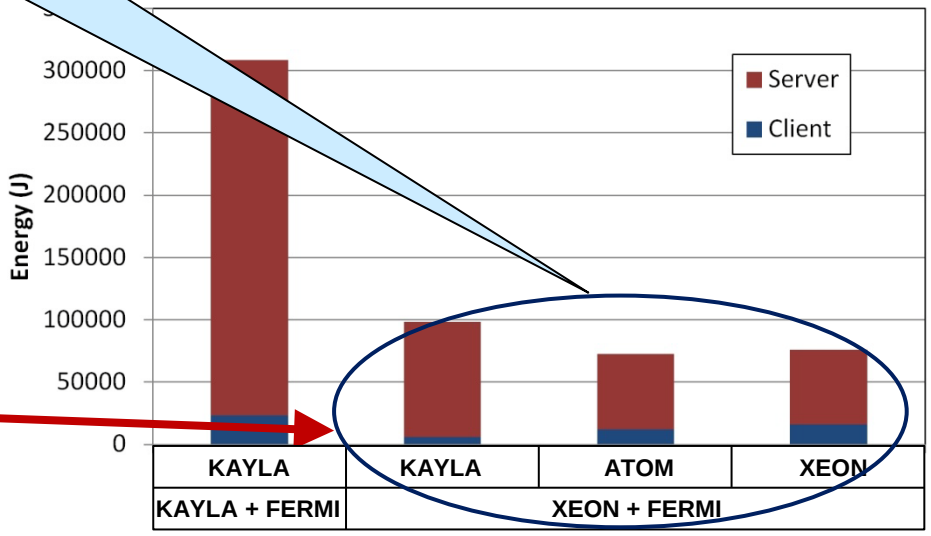
- 2nd analysis: use of **remote GPUs**

LAMMPS



Similar conclusions to CUDASW++ apply to LAMMPS, due to the network bottleneck





Outline

- Current GPU computing facilities
- How GPU virtualization adds value to your cluster
- The rCUDA framework: basics and performance
- Integrating rCUDA with SLURM
- rCUDA and low-power processors
- **rCUDA work in progress**

rCUDA work in progress

- Scheduling in SLURM taking into account the actual GPU utilization
  - Analysis of the benefits of using the SLURM+rCUDA suite in real production clusters with InfiniBand fabric
- Test rCUDA with more applications from *list of "Popular GPU-accelerated Applications"* from NVIDIA
- Support for CUDA 5.5
- Integration of GPUDirect RDMA into rCUDA communications
- Further analyze hybrid ARM-XEON scenarios
  - Use of better network protocols for 1Gbps Ethernet
  - Use of InfiniBand fabrics

http://www.rcuda.net

More than 350 requests

Thanks to Mellanox for its support to this work

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