General-purpose programming on GPU

Exploiting multi-GPU systems

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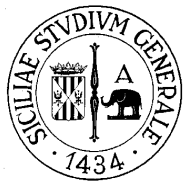

Overview


SLI
GeForce
GeForce
GeForce
CORSAIR
XMS2

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...is it really possible to achieve such (theoretical) peak power?

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We can see a context as a hidden set of settings and structures that are used by the CUDA runtime, when we call a CUDA function like a `cudaMemCpy()`, to answer the question: *which device are we working on? With which settings?*

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It is a recommended practice to call `cudaThreadExit()` at the and of every host thread to explicitly clean up the context.

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Approach n.1 is in most cases the simplest and most efficient one.

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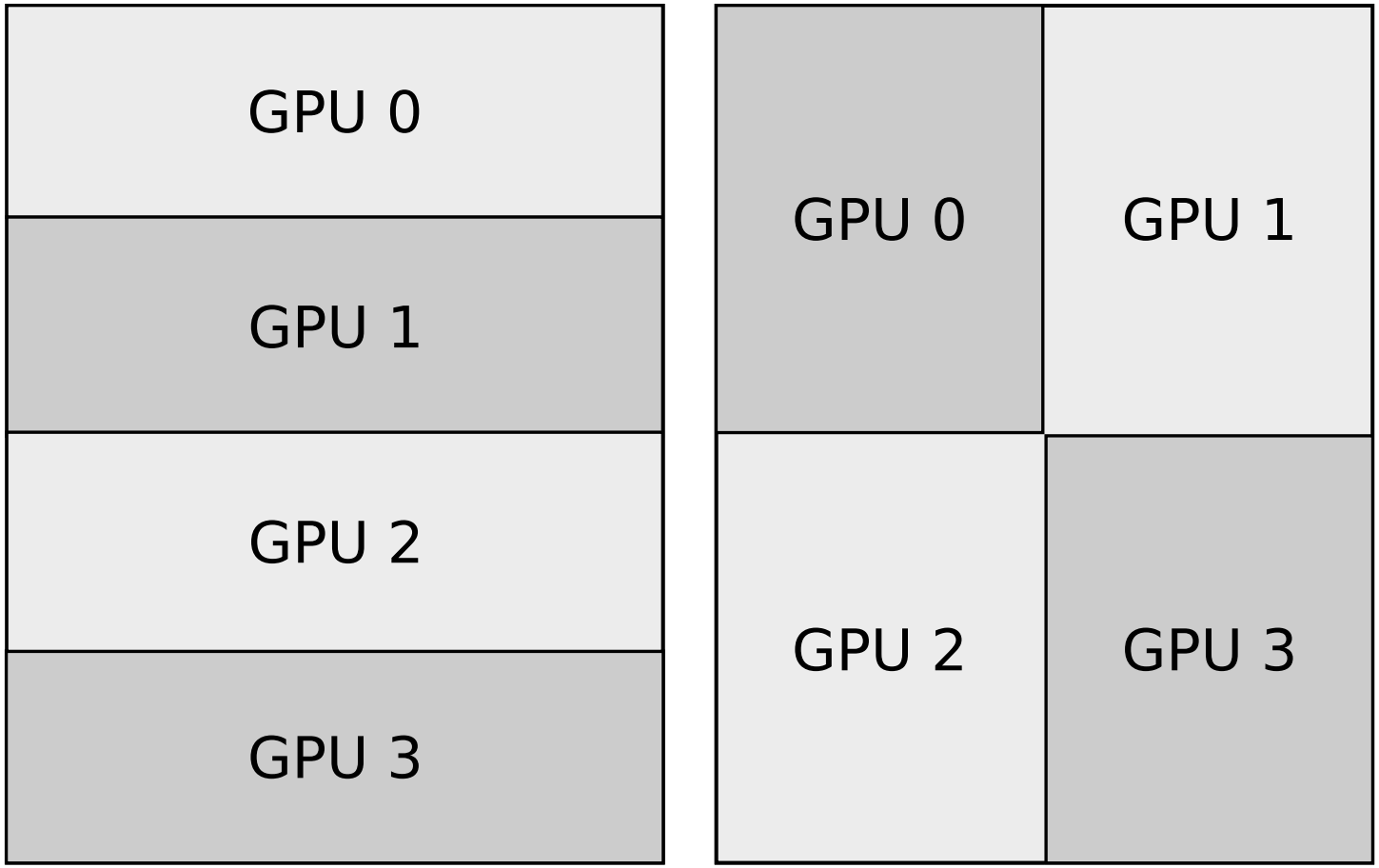

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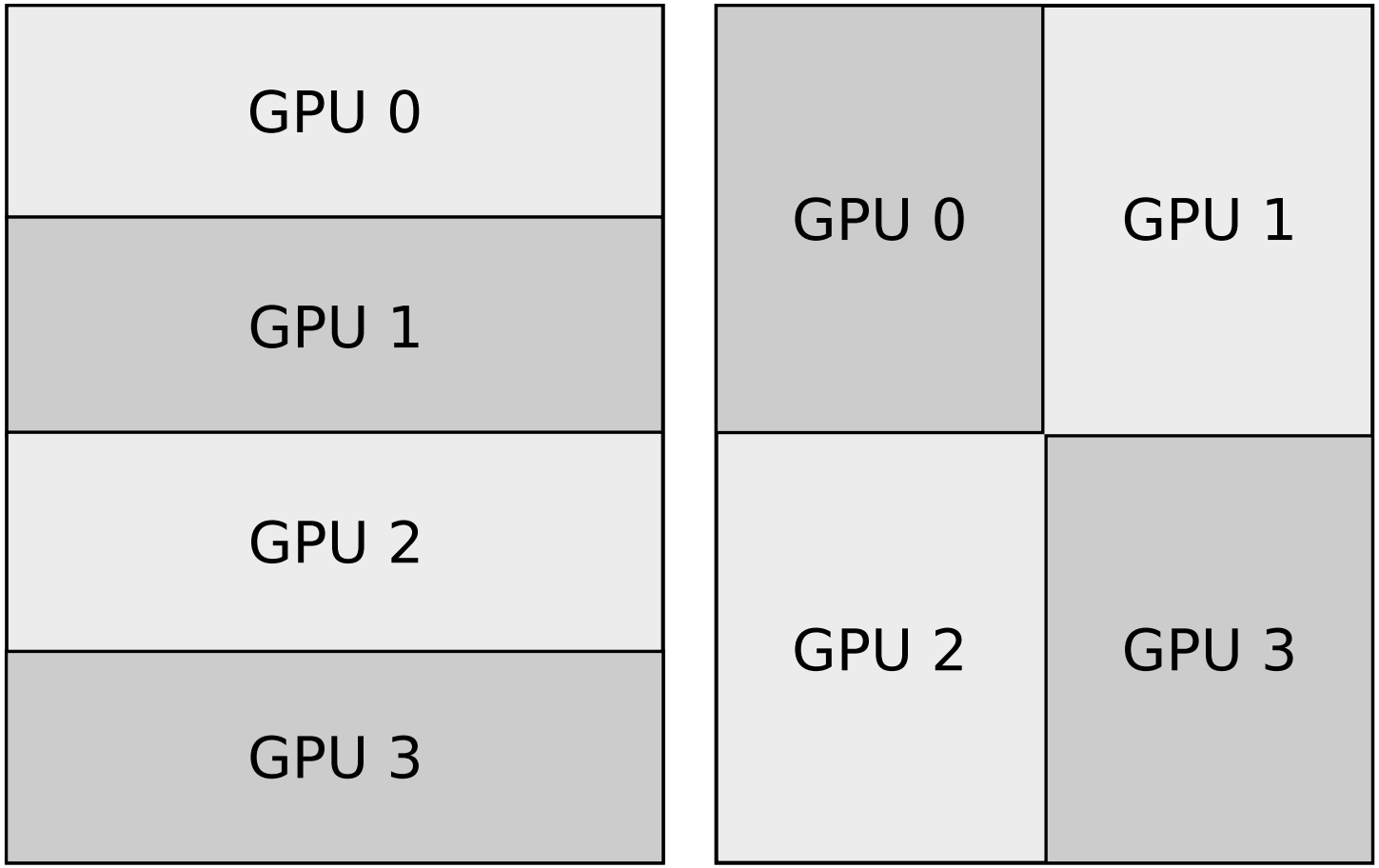
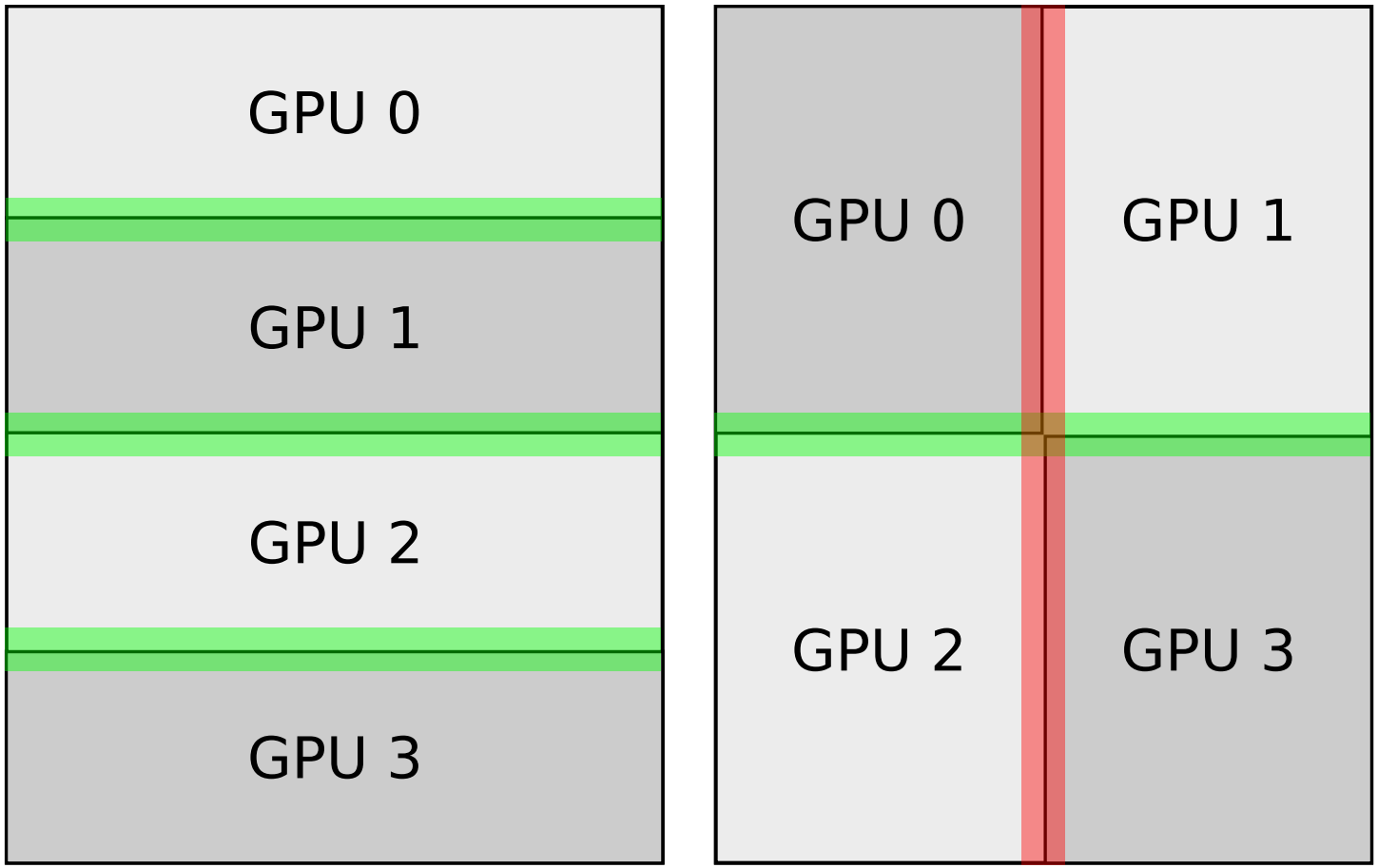


Why first is preferable? When it is not?



Second has a better perimeter/area ratio (i.e. divergences and special cases), however: sparse border accesses (is memory per row?), two neighbors for every GPU (imagine 2x3!)

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Answer: the only general technique is timing *a posteriori*. And it is very complex: requires some basic signal processing to get rid of oscillations and avoid local minima.

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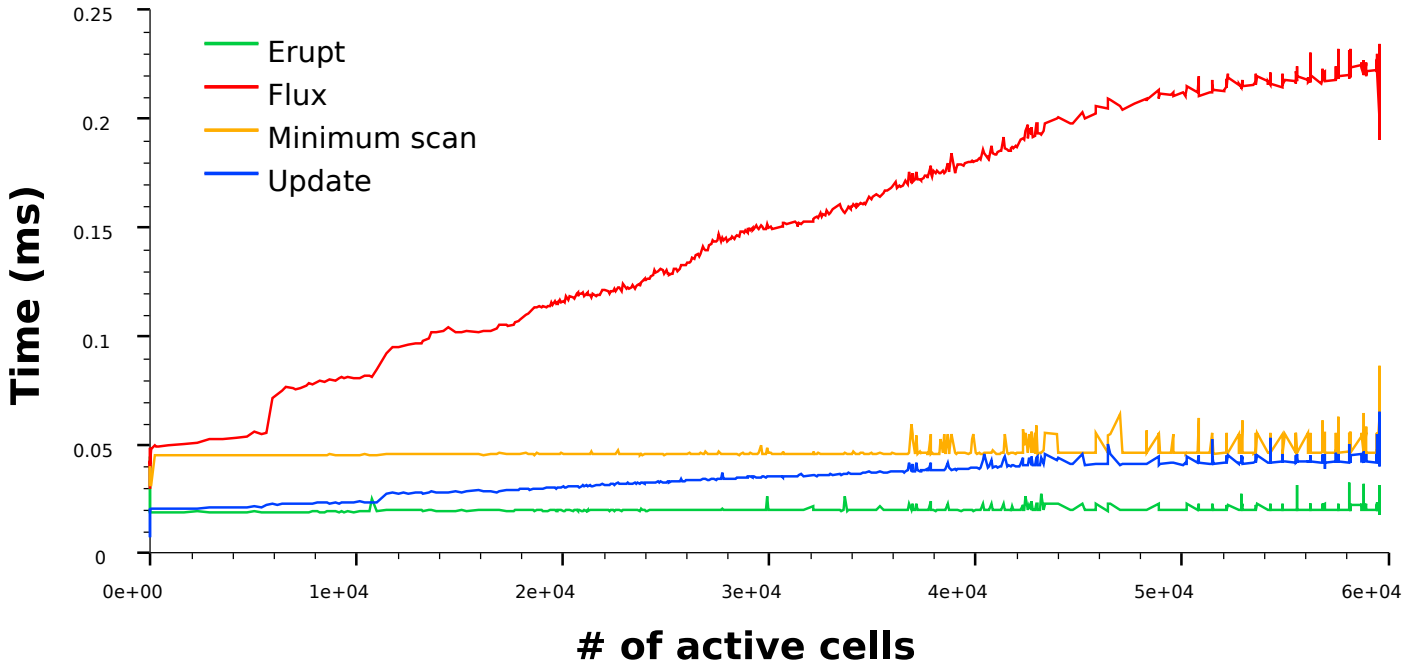
The higher the number of GPUs, the more memory transfers will request exclusive use of PCI bus. The more memory transfers, the less benefits of using multiple GPUs. Need **asynchronous operations** to cover latencies (next lecture).

An example of expected vs. real speedup:



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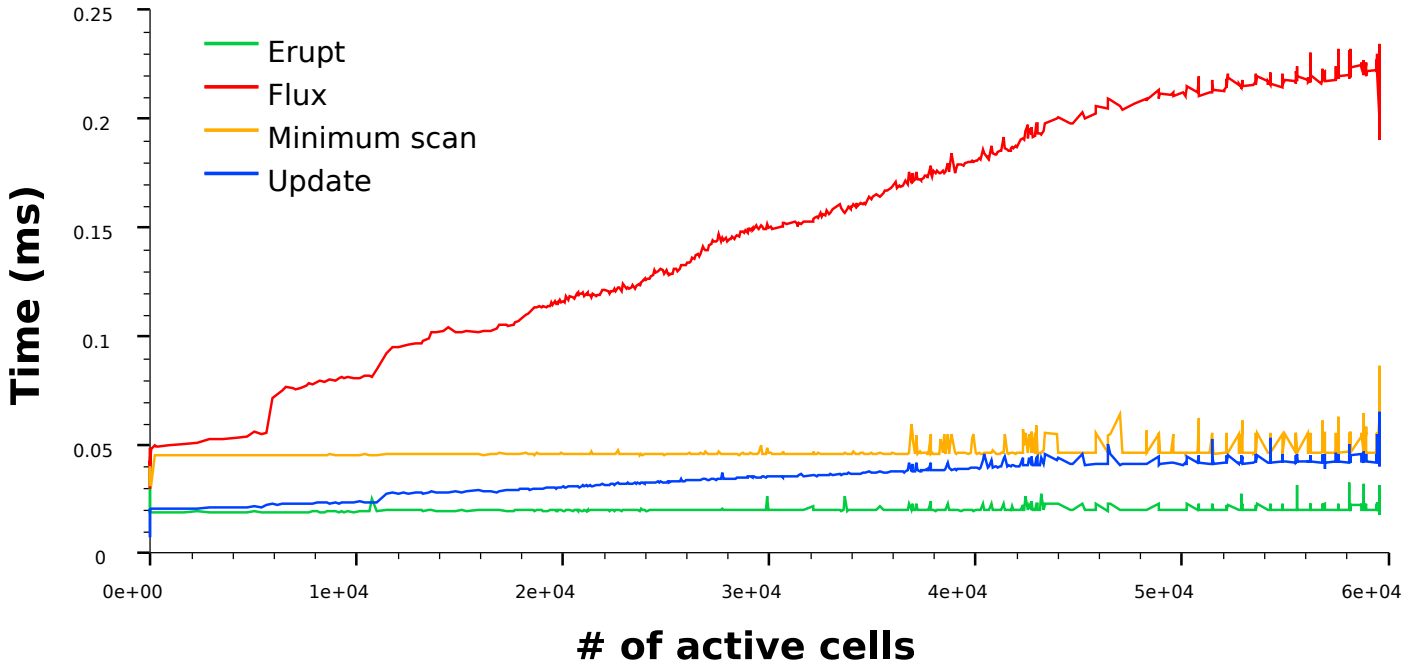

Kernel launch latency and saturation threshold cause

```
time(data/2) > time(data)/2
```

No matter how I split the input data: with K GPUs, in most cases, speedup will be $< K$.

Examples:

- MAGFLOW (image-like)
- SPH (list-like)

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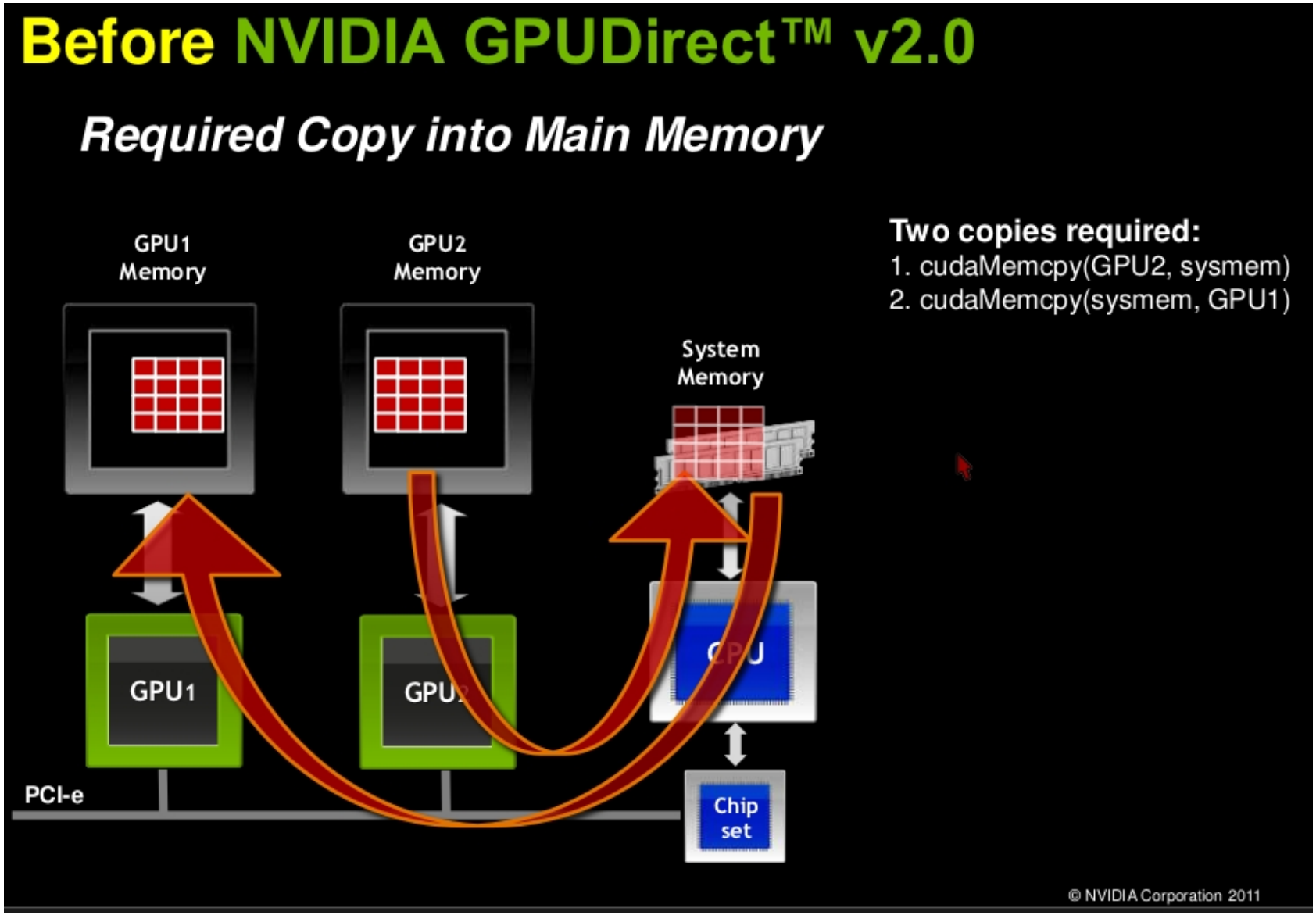
New method to retrieve memory type by address and simpler `cudaMemcpy()` (`cudaMemcpyDefault()`: automatically determine transfer direction)


Before NVIDIA GPUDirect™ v2.0
Required Copy into Main Memory
GPU1 Memory
GPU2 Memory
System Memory
Two copies required:
1. cudaMemcpy(GPU2, sysmem)
2. cudaMemcpy(sysmem, GPU1)
GPU1
GPU2
CPU
PCI-e
Chip set
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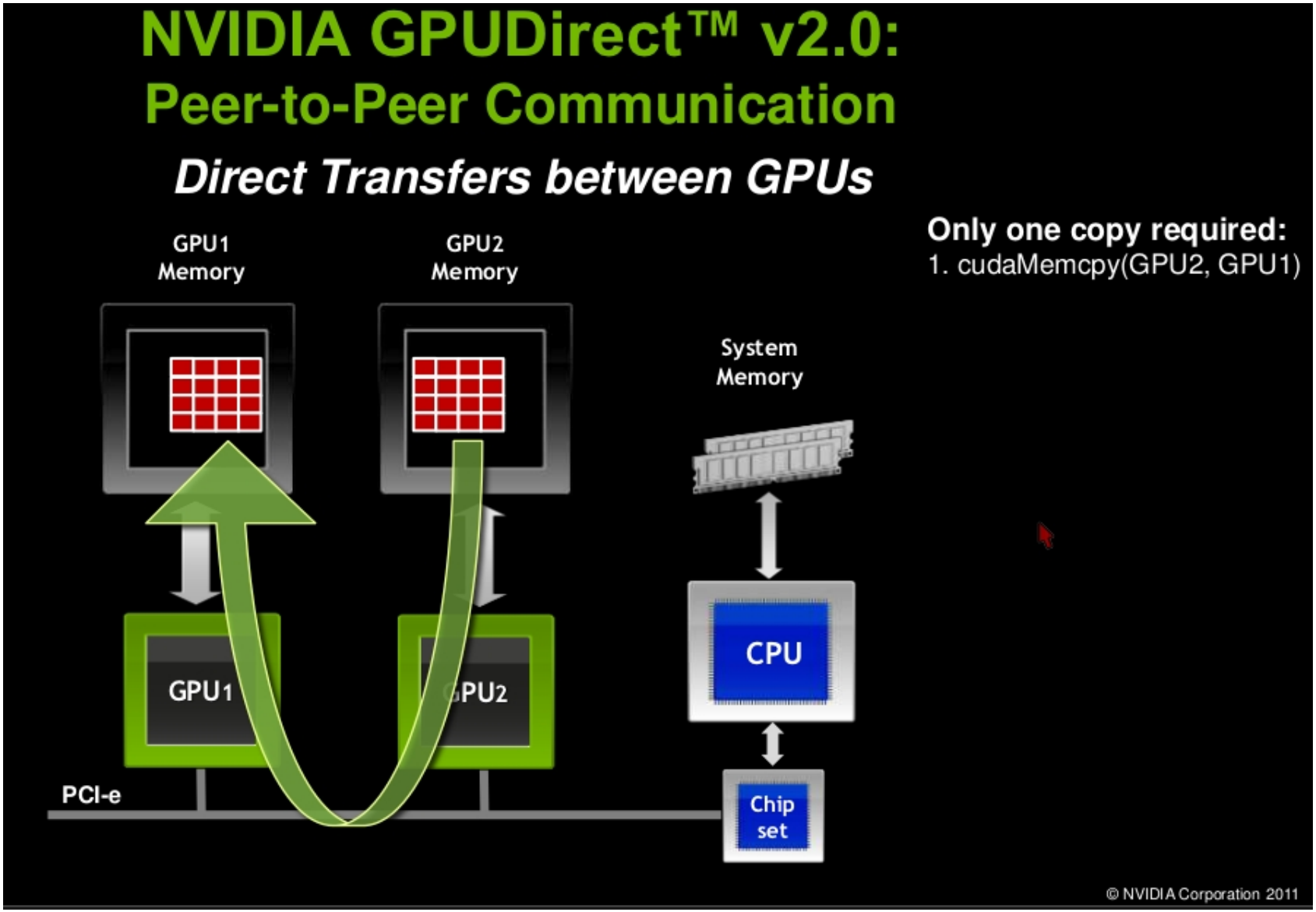
NVIDIA GPUDirect™ v2.0:
Peer-to-Peer Communication
Direct Transfers between GPUs
GPU1 Memory
GPU2 Memory
System Memory
Only one copy required:
1. cudaMemcpy(GPU2, GPU1)
GPU1
GPU2
CPU
PCI-e
Chip set
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