General-purpose programming on GPU
Exploiting multi-GPU systems

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5 CUDA 4
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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 end 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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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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Dynamic *load balancing* may become fundamental to obtain a real speedup. Can you imagine a generic load balancing technique suitable for different applications?

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:

- Erupt
- Flux
- Minimum scan
- Update

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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

Two copies required:
1. cudaMemcpy(GPU2, sysmem)
2. cudaMemcpy(sysmem, GPU1)
NVIDIA GPUDirect™ v2.0: Peer-to-Peer Communication

Direct Transfers between GPUs

Only one copy required:
1. cudaMemcpy(GPU2, GPU1)