Programming paradigms for GPU devices



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Synchronous and Asynchronous API

Concurrent Execution

CPU and GPU interaction

 concurrent execution on CPU and GPU

overlapping transfers and kernels

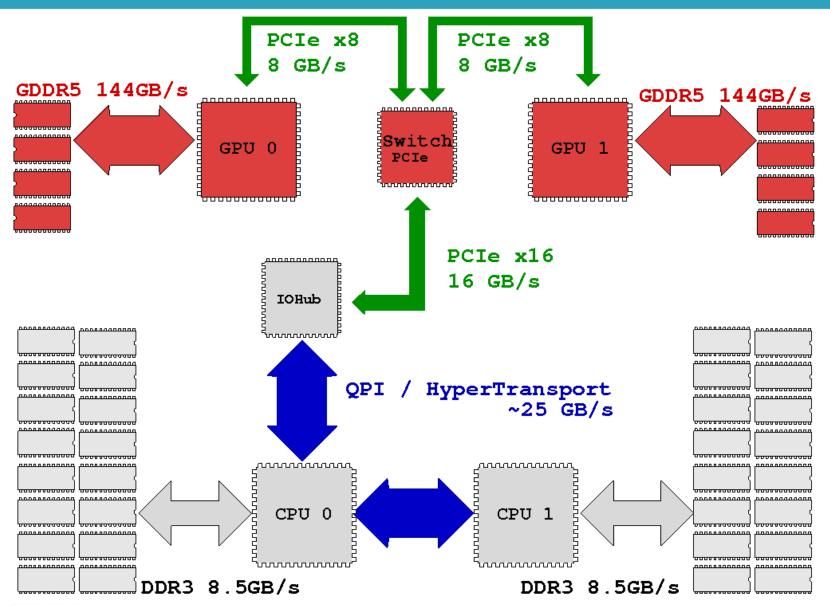
Multi-device management

GPU/GPU interactions





Connection Scheme of host/device





Blocking and Non-blocking Functions

- Every CUDA action is submitted to an execution queue on the device
- CUDA runtime functions can be divided in two categories:
- **blocking** (synchronous): return control to host thread after execution is completed on device
 - all memory transfer > 64KB
 - all memory allocation on device
 - allocation of page locked memory on host

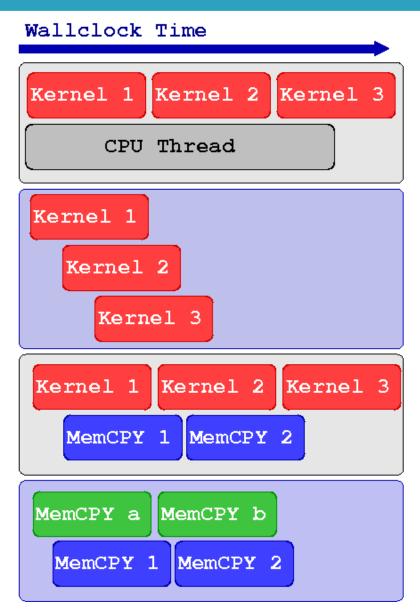
- Non-blocking (asynchronous): return control to host immediatelly, while its execution proceeds on device
 - kernel launches
 - memory transfers < 64KB
 - memory initialization on device (cudaMemset)
 - memory copies from device to device
 - explicit asynchronous memory transfers
- CUDA API provides asynchronous versions of their counterpart synchronous functions
- Asynchronous functions allows to set up concurrent execution of many operations on host and device



Concurrent and Asynchronous Execution

Asynchronous functions allows to expose concurrent executions:

- 1. Overlap computation on *host* and on *device*
- 2. execution of more than one kernel on *device*
- 3. data transfers between host and device while executing a kernel
- 4. data transfers from *host* to *device*, while transfering data from *device* to *host*





Example of Concurrent Execution

```
kernel <<<threads, Blocks>>> (a, b, c)

// work on CPU while GPU is working
CPU_Function()

// Stop CPU until GPU has finished to compute
cudaDeviceSynchronize()

// Use device results on host
CPU_uses_the_GPU_kernel_results()
```

Since CUDA kernel invocation is an asynchronous operation, CPU can proceed and evalutate the CPU_Function()while GPU is involved in kernel execution (concurrent execution).

Before using results from CUDA kernel, synchronization between *host* and *device* is required.



CUDA Streams

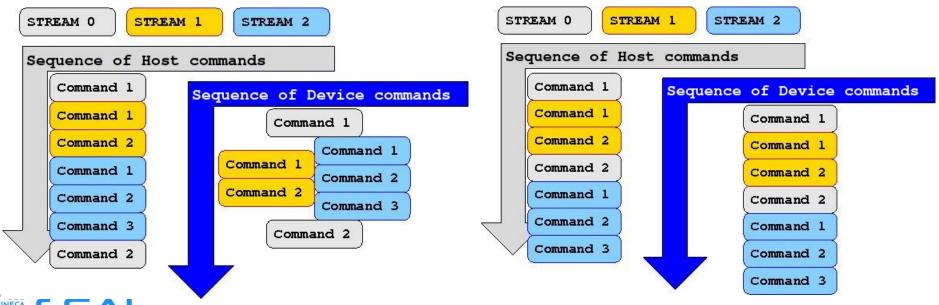
- GPU operations are implementated in CUDA using execution queues, called streams
- Each operation pushed in a stream will be executed only after all other operations in the same stream are completed (FIFO queue behaviour)
- Operations assigned to different streams can be executed in any order with respect each other
- CUDA runtime provides a default stream (aka stream 0) which will be the default queue of all operation if otherwise is not explicitly declared



CUDA Streams

- 1. All operations assigned to the default stream will be executed only after all preceeding operations assigned to other streams are completed
- Any further operation assigned to stream different from default will begin only after all operations on the default stream are completed
- Operations assigned to the default stream act as implicit synchronization barriers among other streams

SuperComputing Applications and Innovation



Synchronization

Explicit Synchronizations :

- cudaDeviceSynchronize()
 - Blocks host code until all operations on device are completed
- cudaStreamSynchronize(stream)
 - Blocks host code until all operations on a stream are completed
- cudaStreamWaitEvent(stream, event)
 - Blocks all operations assigned to a stream until event is reached

Implicit Synchronizations :

- All operations assigned to the default stream
- Page-locked memory allocations
- Memory allocations on device
- Settings operations on device
- . . .



CUDA Streams Management

Stream management:

• Constructor: cudaStreamCreate()

• Synchronization: cudaStreamSynchronize()

• **Destructor:** cudaStreamDestroy()

- Stream allows various execution modes, depending on the compute capability:
 - concurrent execution of more than one kernel per GPU
 - concurrent asynchronous data transfers in both H2D and D2H directions
 - concurrent execution on device/host and data transfers from host and device



Kernel Concurrent Execution

```
cudaStreamCreate(stream1)
cudaStreamCreate(stream2)
// concurrent execution of the same kernel
Kernel_1<<<bloomblocks, threads, SharedMem, stream1>>>(inp_1, out_1)
Kernel_1<<<bloomblocks, threads, SharedMem, stream2>>>(inp_2, out_2)
// concurrent execution of different kernels
Kernel_1<<<bloomblocks, threads, SharedMem, stream1>>>(inp, out_1)
Kernel_2<<<bloomblocks, threads, SharedMem, stream2>>>(inp, out_2)
cudaStreamDestroy(stream1)
cudaStreamDestroy(stream2)
```



Asynchronous Data Transfers

- In order to performe asynchronous data transfers between host and device the host memory must be of page-locked type (a.k.a pinned)
- CUDA runtime provides the following functions to handle pagelocked memory:
 - cudaMallocHost()allocate page-locked memory on *host*
 - cudaFreeHost()free page-locked allocated memory on *host*
 - cudaHostRegister()turn host allocated memory into page-locked
 - cudaHostUnregister()turn page-locked memory into ordinary memory
- cudaMemcpyAsync()function explicitly performes asynchronous data transfers between host and device memory
- Data transfer operations must queued into a stream different from the default one in order to be asynchronous
- Using page-locked memory allows data transfers between host and device memory with higher bandwidth



Asynchronous Data Transfers

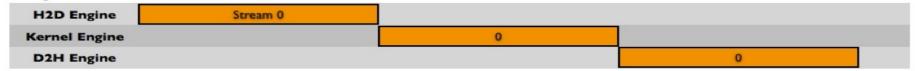
```
cudaStreamCreate(stream_a)
cudaStreamCreate(stream_b)
cudaMallocHost(h_buffer_a, buffer_a_size)
cudaMallocHost(h_buffer_b, buffer_b_size)
cudaMalloc(d_buffer_a, buffer_a_size)
cudaMalloc(d_buffer_b, buffer_b_size)
// concurrent and asynchronous data transfer H2D and D2H
cudaMemcpyAsync(d_buffer_a, h_buffer_a, buffer_a_size,
cudaMemcpyHostToDevice, stream_a)
cudaMemcpyAsync(h_buffer_b, d_buffer_b, buffer_b_size,
cudaMemcpyDeviceToHost, stream b)
cudaStreamDestroy(stream_a)
cudaStreamDestroy(stream_b)
cudaFreeHost(h_buffer_a)
cudaFreeHost(h buffer b)
```



Asynchronous Data Transfers

```
cudaStream_t stream[4];
for (int i=0; i<4; ++i) cudaStreamCreate(&stream[i]);</pre>
float* hPtr; cudaMallocHost((void**)&hPtr, 4 * size);
for (int i=0; i<4; ++i) {
  cudaMemcpyAsync(d_inp + i*size, hPtr + i*size,
                  size, cudaMemcpyHostToDevice, stream[i]);
 MyKernel << 100, 512, 0, stream[i] >>> (d_out+i*size, d_inp+i*size, size);
  cudaMemcpyAsync(hPtr + i*size, d_out + i*size,
                  size, cudaMemcpyDeviceToHost, stream[i]);
cudaDeviceSynchronize();
for (int i=0; i<4; ++i) cudaStreamDestroy(&stream[i]);
```

Sequential Version



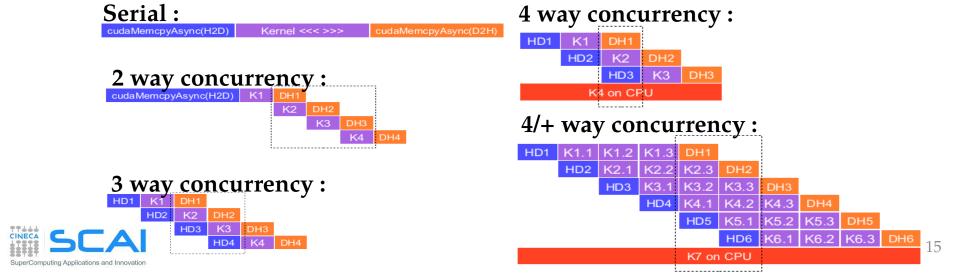
Asynchronous Versions

H2D Engine	gine	1	2	3	4	
Kernel Engine	ngine		1	2	3	4
D2H Engine	gine			- 1	2	3



Concurrency

- Concurrency: when two or more CUDA operations proceed at the same time
 - Fermi: up to 16 kernel CUDA / Kepler: up to 32 kernel CUDA
 - 2 data transfers host/device (duplex)
 - concurrency with host operations
- Requirements for concurrency:
 - operations must be assigned to streams different from the default stream
 - host/device data transfers should be asynchronous and host memory must be pagelocked
 - only if there are enough hw resources left to use (SharedMem, Registers, Blocks, PCIe bus, ...)
 - No kernel concurrency if all SM on the device are in use
 - data transfers won't take place if other transfers are still going on



Stream Priorities

- Relative priorities of streams can be specified at creation
- If not specified, all streams get the same priority
- runtime will choose which operation start first among equivalent priority streams

```
// get the range of stream priorities for this device
int priority_high, priority_low;
cudaDeviceGetStreamPriorityRange(&priority_low, &priority_high);

// create streams with highest and lowest priorities
cudaStream_t st_high, st_low;
cudaStreamCreateWithPriority(&st_high, cudaStreamNonBlocking,
priority_high);
cudaStreamCreateWithPriority(&st_low, cudaStreamNonBlocking,
priority_low);
```



Device Management

CUDA runtime allows to control more than one GPU device available on a computing node (multi-GPU programming):

- CUDA 3.2 and previous versions
 - a multi-thread or multi-process parallel paradigm was required to access and use more than one device
- CUDA 4.0 and later versions
 - new runtime API to select and to control all available devices from a serial program (single host core)
 - you can still use a parallel programming approach (multi-thread or multi-process):
 - each process or thread will be always able to access all devices
 - you can select which devices a thread/process can control



Device Management

```
cudaDeviceCount(number_gpu)
cudaGetDeviceProperties(gpu_property, gpu_ID)

cudaSetDevice(0)
kernel_0 <<<threads, Blocks>>> (a, b, c)

cudaSetDevice(1)
kernel_1 <<<threads, Blocks>>> (d, e, f)

For each device:
   cudaSetDevice(device)
   cudaDeviceSynchronize()
```

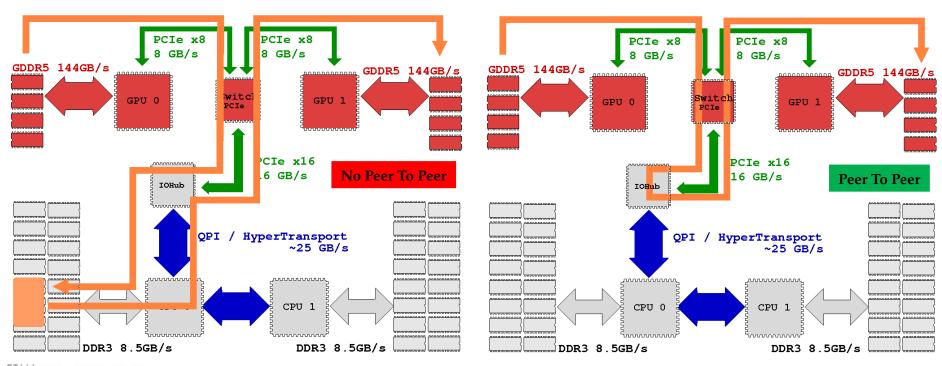
CUDA runtime allows to:

- get information on available CUDA enabled devices
- get properties of each CUDA device (cc, memory sizes, clock, etc)
- select a device and queue CUDA operations on that device
- manage synchronization among available devices



Peer to Peer Transfers

- A device can directly transfer or access data to/from another device
- This kind of direct transfer is called Peer to Peer (P2P)
- P2P transfers are more efficient and do not require a host buffer
- Direct access avoid host memory copy





Peer to Peer Transfer Pseudocode

```
gpuA=0, gpuB=1
cudaSetDevice(gpuA)
cudaMalloc(buffer_A, buffer_size)
cudaSetDevice(gpuB)
cudaMalloc(buffer_B, buffer_size)
cudaSetDevice(gpuA)
cudaDeviceCanAccessPeer(answer, gpuA, gpuB)
If answer is true:
cudaDeviceEnablePeerAccess(gpuB, 0)
// gpuA performs copy from gpuA to gpuB
cudaMemcpyPeer(buffer_B, gpuB, buffer_A, gpuA, buffer_size)
// gpuA performs copy from gpuB to gpuA
cudaMemcpyPeer(buffer_A, gpuA, buffer_B, gpuB, buffer_size)
```



Peer to Peer Direct Access Pseudocode

```
gpuA=0, gpuB=1
cudaSetDevice(gpuA)
cudaMalloc(buffer_A, buffer_size)
cudaSetDevice(gpuB)
cudaMalloc(buffer_B, buffer_size)
cudaSetDevice(gpuA)
cudaDeviceCanAccessPeer(answer, gpuA, gpuB)
If answer is true:
cudaDeviceEnablePeerAccess(gpuB, 0)
// gpuA invokes a kernel that accesses to gpuB memory
kernel<<<threads, blocks>>>(buffer_A, buffer_B)
```



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