General-purpose programming on GPU

Asynchronous operations

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Overview

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Moreover: in multi-GPU applications with minimum problem interdependence, say n the number of GPUs, a typical need is $4 \cdot (n - 1)$ transfer requests per frame (why?)

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Programming guide states that *when an application is run via a CUDA debugger or profiler all launches are synchronous*, but...

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There are three requirements for async memcpys: **page-locked** host memory, use of **streams** and `-async` calls.

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Allocating too much page-locked memory may decrease overall system performance; it is critical to allocate less space than physical memory.

CUDA offers two simple methods to easily allocate page-locked memory, and one to free it:

```
cudaError_t cudaMallocHost(void **ptr,
    size_t size [, unsigned int flags]);

cudaError_t cudaHostAlloc(void **pHost,
    size_t size, unsigned int flags);

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```

`cudaMallocHost()` is a special case of `cudaHostAlloc()` with default parameters: in reference manual, there is no mention to `flags` for `cudaMallocHost()` (official reason: C/C++ interoperability?).

Flags:

`cudaHostAllocDefault` : default settings; causes `cudaHostAlloc()` to emulate `cudaMallocHost()`

`cudaHostAllocPortable` : allocated memory is available to all CUDA contexts, even if created before; the default is that only allocating thread may access it

`cudaHostAllocMapped` : maps the allocation into the CUDA address space (see later)

`cudaHostAllocWriteCombined` : disable caching of mapped memory

Example:

```
#define DIM (1024*1024)
float *harray, *harray_map;
err = cudaMallocHost(&harray, sizeof(float)*DIM);
err = cudaHostAlloc(&harray_map,
    sizeof(float)*DIM,
    cudaHostAllocPortable | cudaHostAllocMapped);
```

...

```
error = cudaFreeHost(harray);
error = cudaFreeHost(harray_map);
```

Overview

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When stream is not specified to a kernel or memcpy operation, the default one (0) is used and operations are not concurrent.

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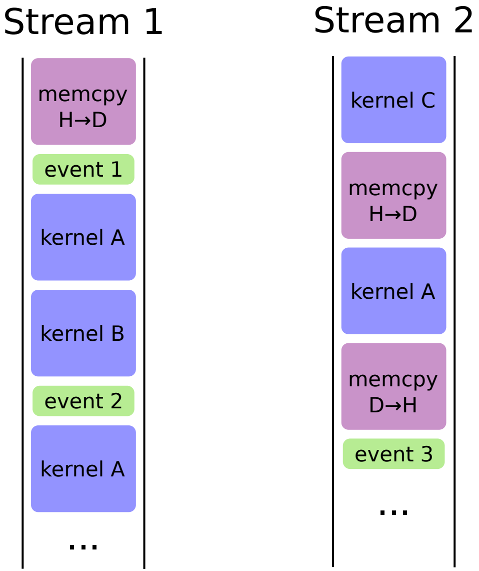
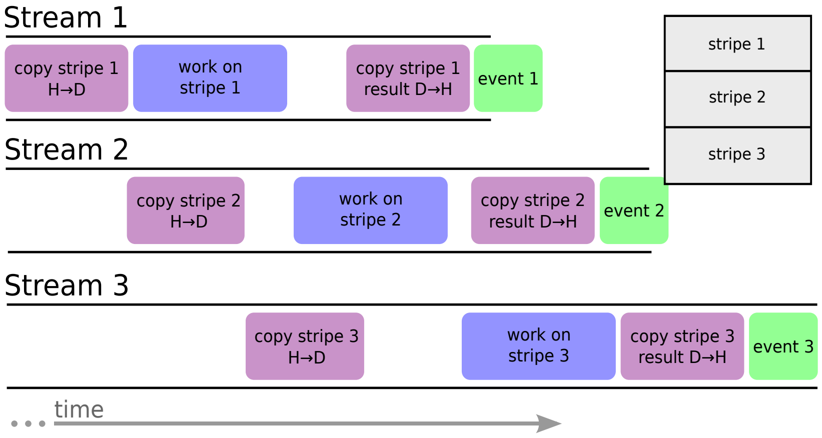
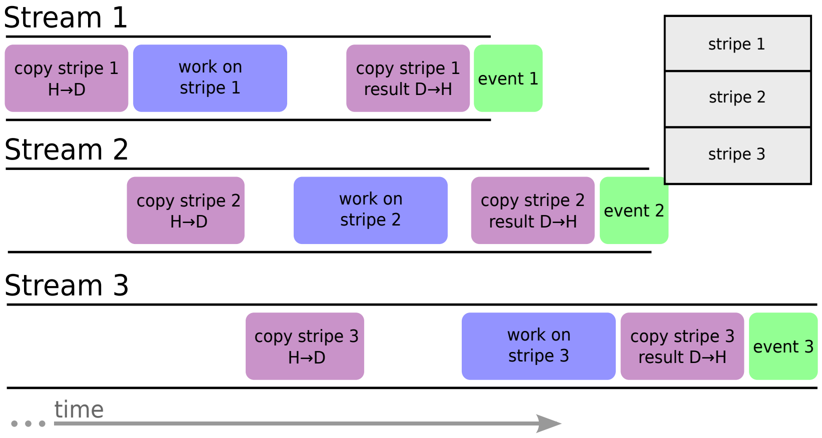
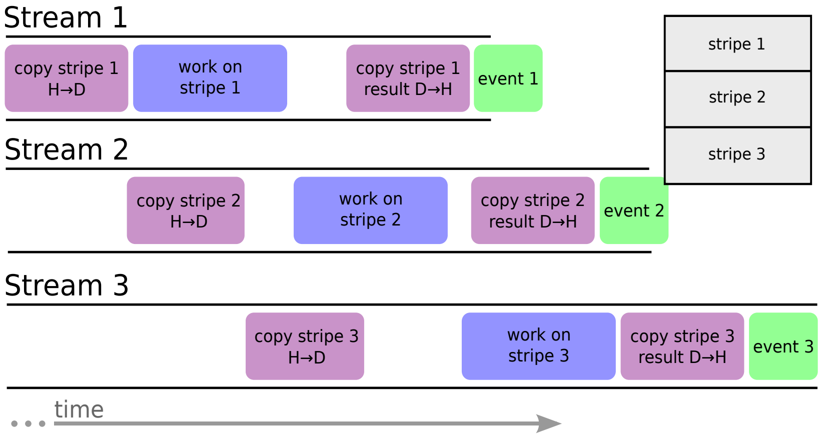
It not possible to create a real dependency graph, but with an appropriate usage of events it is possible to ensure quite complicated dependencies.


Stream 1
memcpy H→D
event 1
kernel A
kernel B
event 2
kernel A
...
Stream 2
kernel C
memcpy H→D
kernel A
memcpy D→H
event 3
...


Stream 1
copy stripe 1 H→D
work on stripe 1
copy stripe 1 result D→H
event 1
Stream 2
copy stripe 2 H→D
work on stripe 2
copy stripe 2 result D→H
event 2
Stream 3
copy stripe 3 H→D
work on stripe 3
copy stripe 3 result D→H
event 3
stripe 1
stripe 2
stripe 3
. . . time



- One kernel at a time is executing



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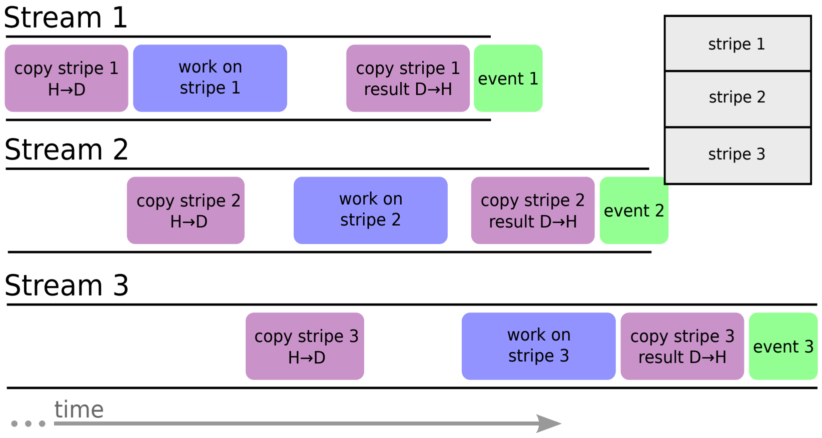

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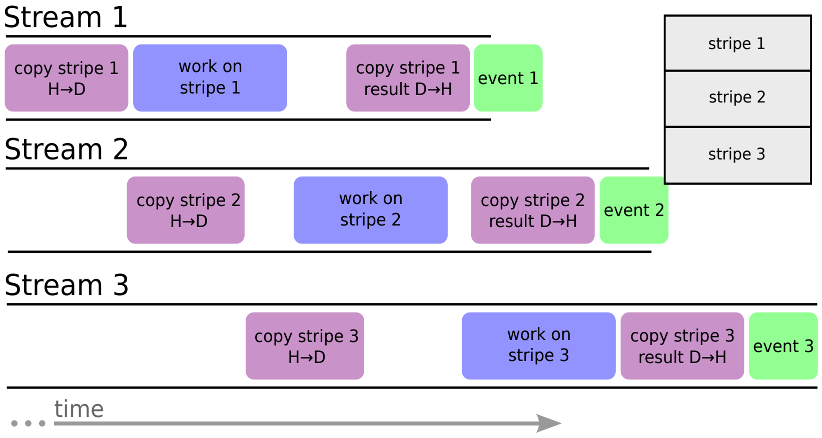
- One memcpy at a time is executing
- Kenel and memcpys in different streams execute concurrently!



Kernel total time is the same as it was non concurrent; but download and upload times are partially covered, reducing total transfer time from $2 \cdot t$ to $2 \cdot \frac{t}{3}$.
See timeline profiling of SDK samepl simpleStreams

To enqueue a kernel launch in a given stream with high level API, pass the stream as the fourth parameter:

```
cudaStreamCreate(&mystream);
...
my_kernel<<< numBlocks, numThreads,
    0, mystream>>> ( [args] );
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Memory transfer methods are identical but with a `stream` parameter and -async suffix:

```
cudaError_t cudaMemcpyAsync(
    void *dst,
    const void *src,
    size_t count,
    enum cudaMemcpyKind kind,
    cudaStream_t stream=0);
```

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There is a `-async` version of every memcpy method. Note default null stream

Let's see a typical usage example.

Creation:

```
#define NSTREAMS 4
cudaStream_t stream[NSTREAMS];
for (int i = 0; i < NSTREAMS; ++i)
    cudaStreamCreate(&stream[i])
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```

Destruction:

```
for (int i = 0; i < NSTREAMS; ++i)
    cudaStreamDestroy(stream[i]);
```

Enqueueing:

```
// use multiple for cycles: prefer breadth first
for (int i = 0; i < NSTREAMS; ++i)
    cudaMemcpyAsync(inputDevPtr + i * size,
        hostPtr + i * size, size,
        cudaMemcpyHostToDevice, stream[i]);

for (int i = 0; i < NSTREAMS; ++i)
    MyKernel<<<100, 512, 0, stream[i]>>>
        (outputDevPtr + i * size,
        inputDevPtr + i * size, size);

for (int i = 0; i < NSTREAMS; ++i)
    cudaMemcpyAsync(hostPtr + i * size,
        outputDevPtr + i * size, size,
        cudaMemcpyDeviceToHost, stream[i]);
```

Synchronization:

```
// Wait for compute device to finish
cudaError_t cudaThreadSynchronize();

// Wait for a stream to complete everything
cudaError_t cudaStreamSynchronize(cudaStream_t stream);

// Waits for an event to complete
cudaError_t cudaEventSynchronize(cudaEvent_t event);

// Makes the given stream to wait for given
// event before any future operation is
// starte (inter-stream synchronization)
cudaError_t cudaStreamWaitEvent(cudaStream_t stream,
    cudaEvent_t event, unsigned int flags);
```

See the programming guide for more methods (e.g. queries) and implicit synchronization mechanisms

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No operations are checked but the first in every queue. This means that **operations enqueued with a depth-first policy will be executed serially**.

(queue scheme)

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In these special cases, do we really need explicit transfers?

If we allocate a host buffer with flag `cudaHostAllocMapped` the buffer is prepared to be *mapped* to a subrange of the address space of thedevice; then, we can obtain a device pointer, pointing to the same physical address, with `cudaHostGetDevicePointer()`:

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```
// flags must be 0
cudaError_t cudaHostGetDevicePointer(
    void **pDevice, void *pHost,
    unsigned int flags);
```

```
// alloc buffer
cudaHostAlloc((void**)&host_array,
    sizeof(float)*SIZE, cudaHostAllocMapped);

// init data
for(i=0; i < SIZE; i++)
    host_array[i]=(float)rand();

// get mapped pointer (flags must be 0)
cudaHostGetDevicePointer((void**)&device_pointer,
    (void*)host_array, 0);

// launch kernel: direct access to buffer!
vectorAdd<<<nblocks, nthreads>>>
    (device_pointer, SIZE);
```

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Standing on the programming guide, reading from a "write combined" buffer may be much faster (up to 40%), but writing on it from host may be expensive. It is recommended only when device reads alot, host writes only once.

Hands on code: aynchronous operations & timeline profiling