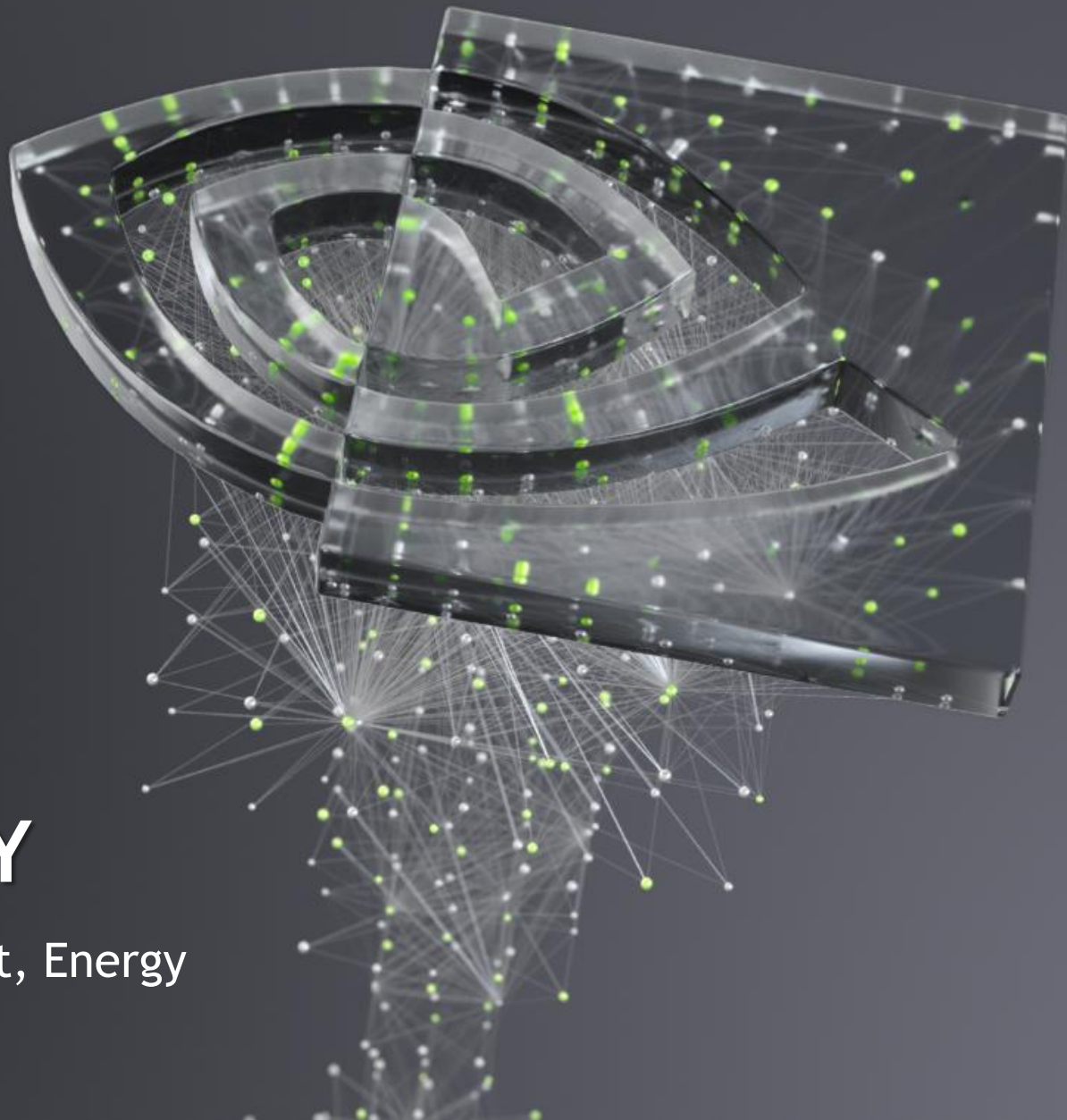




CUDA CONCURRENCY

Guillaume Barnier, Solutions Architect, Energy
gbarnier@nvidia.com



AGENDA

Concurrency- motivation

Pinned memory

CUDA Streams

Overlap of copy and compute

Use case: vector math/video processing pipeline

Additional stream considerations

Copy-compute overlap with managed memory

multi-GPU concurrency

Other concurrency scenarios: kernel concurrency,
host/device concurrency

further study

homework

MOTIVATION

Recall 3 steps from session 1...

Naïve implementation leads to a processing flow like this:

1. Copy data to the GPU

2. Run kernel(s) on GPU

3. Copy results to host

duration

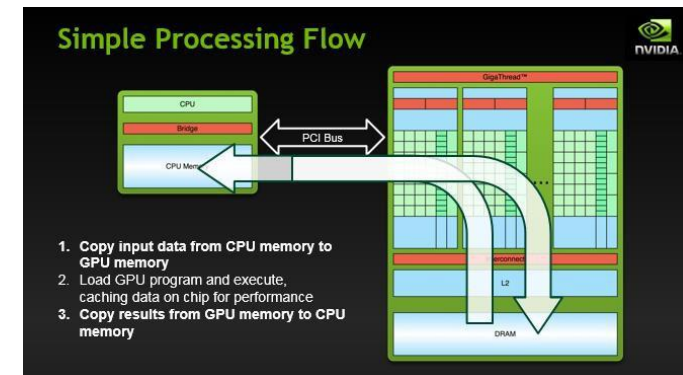
->Wouldn't it be nice if we could do this:

1. Copy data to the GPU

2. Run kernel(s) on GPU

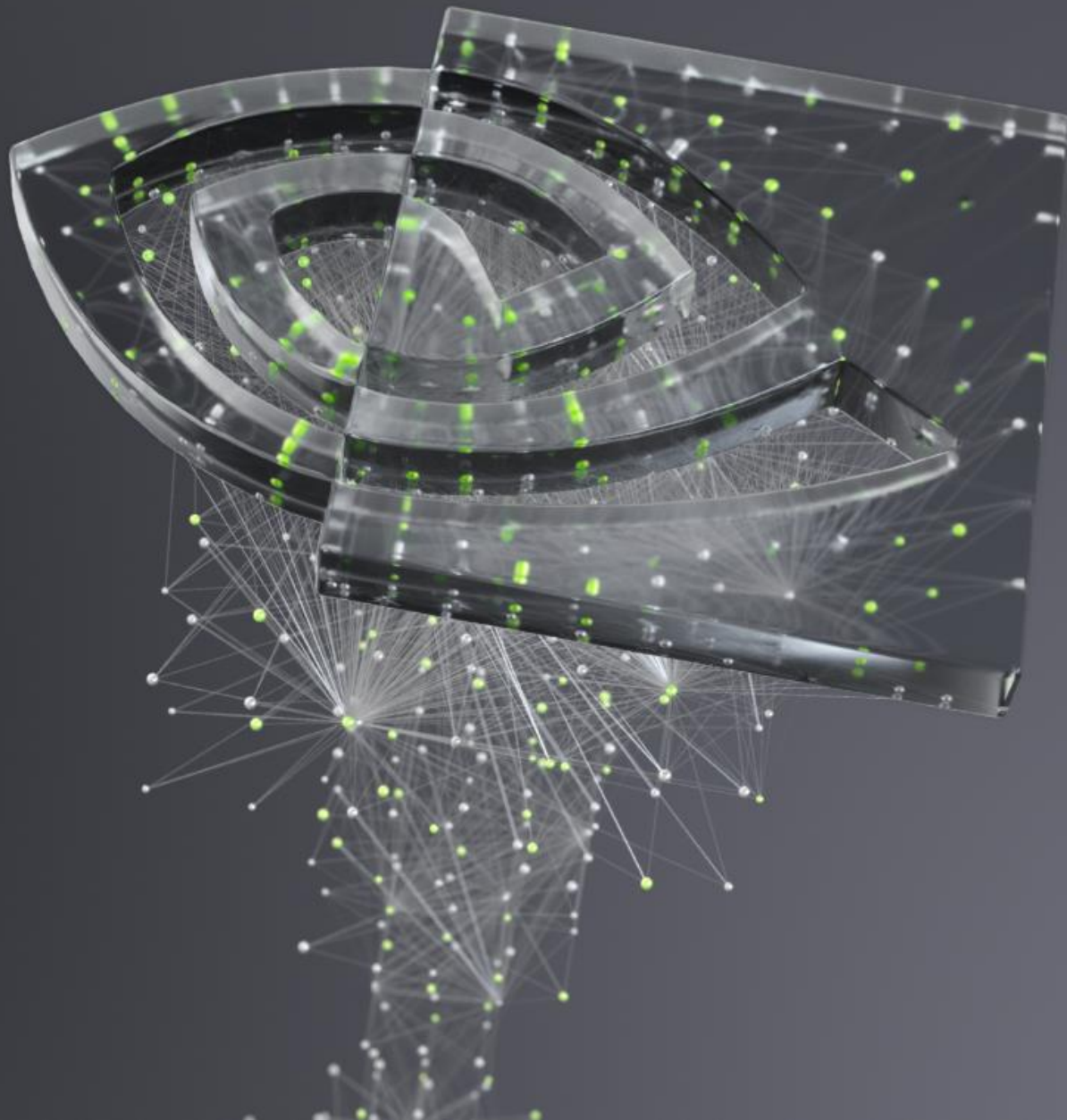
3. Copy results to host

duration





PINNED MEMORY

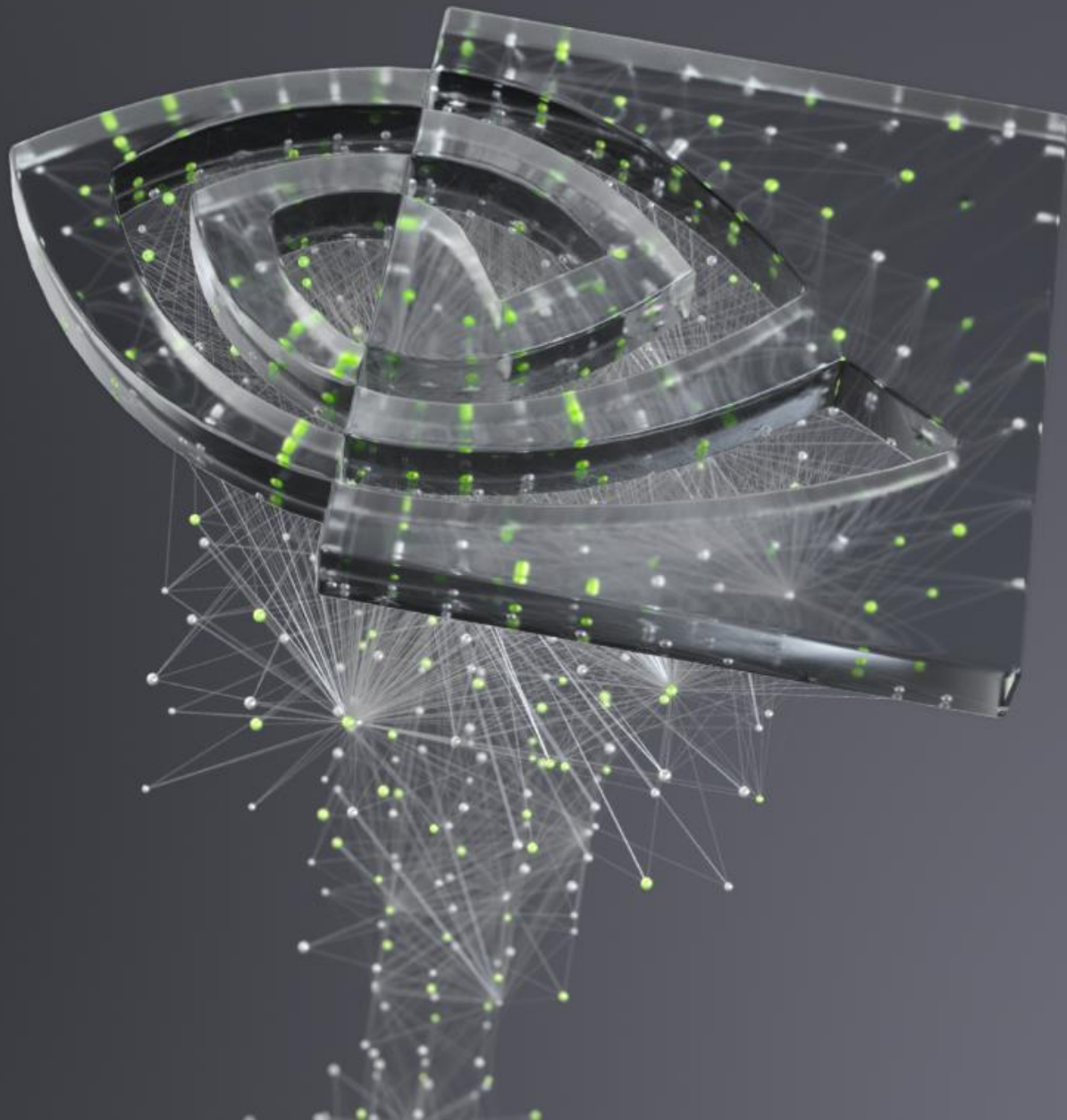


Pinned (non-pageable) memory

- Pinned memory enables:
 - faster Host<->Device copies
 - memcpy asynchronous with CPU
 - memcpy asynchronous with GPU
- Usage
 - `cudaHostAlloc` / `cudaFreeHost`
instead of `malloc` / `free` or `new` / `delete`
 - `cudaHostRegister` / `cudaHostUnregister`
pin regular memory (e.g. allocated with `malloc`) after allocation
- Implication:
 - pinned memory is essentially removed from host virtual (pageable) memory



CUDA STREAMS



Streams and Async API Overview

- **Default API:**
 - Kernel launches are asynchronous with CPU
 - `cudaMemcpy` (D2H, H2D) block CPU thread
 - CUDA calls are serialized by the driver (legacy default stream)
- **Streams and async functions provide:**
 - `cudaMemcpyAsync` (D2H, H2D) asynchronous with CPU
 - Ability to concurrently execute a kernel and a memcpy
 - Concurrent copies in both directions (D2H, H2D) possible on devices with at least 2 copy engines
- **Stream: sequence of operations that execute in issue-order on GPU**
 - Operations from different streams may be interleaved
 - A kernel and memcpy from different streams can be overlapped

Stream Semantics

- **Two operations issued into the same stream will execute in issue-order.**
 - Operation B issued after operation A will not begin to execute until operation A has completed
- **Two operations issued into separate streams have no ordering prescribed by CUDA**
 - Operation A issued into stream 1 may execute before, during, or after operation B issued into stream 2
- **What do we mean by “operation”?**
 - Usually, `cudaMemcpyAsync` or a `kernel call`
 - More generally, most CUDA API calls that take a stream parameter, as well as stream callbacks

Stream creation and copy/compute overlap

- **Requirements:**
 - D2H or H2D memcopy from pinned memory
 - Kernel and memcopy in different, non-0 streams
- **Code**

```
cudaStream_t stream1, stream2;  
cudaStreamCreate(&stream1);  
cudaStreamCreate(&stream2);
```

```
cudaMemcpyAsync(dst, src, size, dir, stream1);  
kernel<<<grid, block, 0, stream2>>>(...);
```

Potentially
overlapped

```
cudaStreamQuery(stream1);           // Check if stream is idle  
cudaStreamSynchronize(stream2);    // CPU waits until all operations on stream2 are completed  
cudaStreamDestroy(stream2);
```

Stream Examples



K1,M1,K2,M2:



K1,K2,M1,M2:



K1,M1,M2:



K1,M2,M1:



K1,M2,M2:

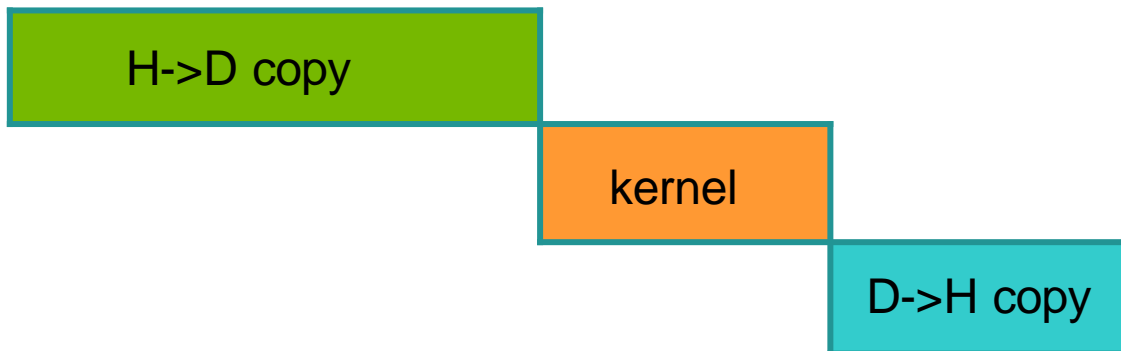


K: Kernel
M: Memcopy
Integer: Stream ID

Time

Example stream behavior for vector math

(assumes algorithm decomposability)



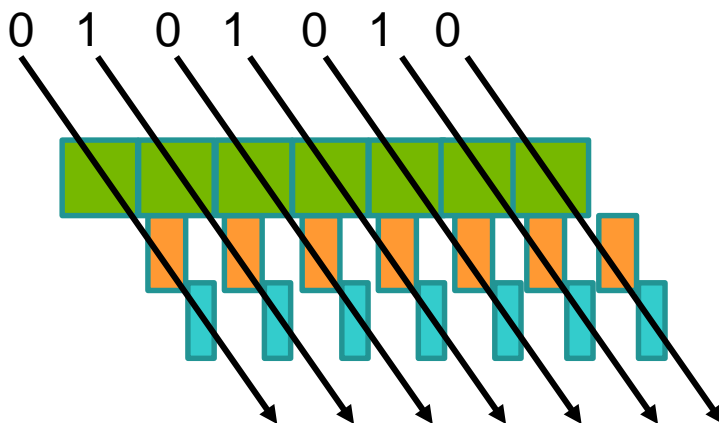
non-streamed

```
cudaMemcpy(d_x, h_x, size_x,  
cudaMemcpyHostToDevice);  
kernel<<<b, t>>>(d_x, d_y, N);  
cudaMemcpy(h_y, d_y, size_y,  
cudaMemcpyDeviceToHost);
```

streamed

```
for (int i = 0, i<c; i++){  
    size_t offx = (size_x/c)*i;  
    size_t offy = (size_y/c)*i;  
    cudaMemcpyAsync(d_x+offx, h_x+offx,  
size_x/c, cudaMemcpyHostToDevice,  
stream[i%ns]);  
    kernel<<<b/c, t, 0,  
stream[i%ns]>>>(d_x+offx, d_y+offy,  
N/c);  
    cudaMemcpyAsync(h_y+offy, d_y+offy,  
size_y/c, cudaMemcpyDeviceToHost,  
stream[i%ns]);}
```

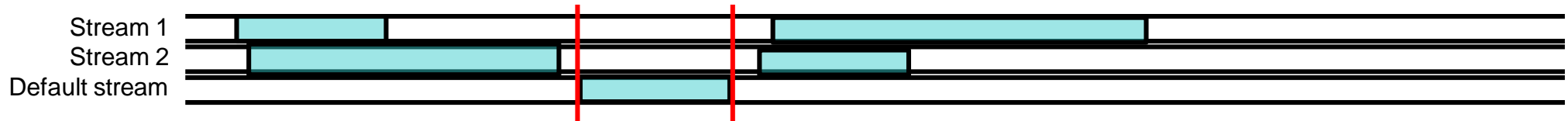
Stream ID:



Similar: video processing pipeline

Default Stream

- Kernels or `cudaMemcpy`... that do not specify stream (or use 0 for stream) are using the default stream
- Legacy default stream behavior: synchronizing (on the device):



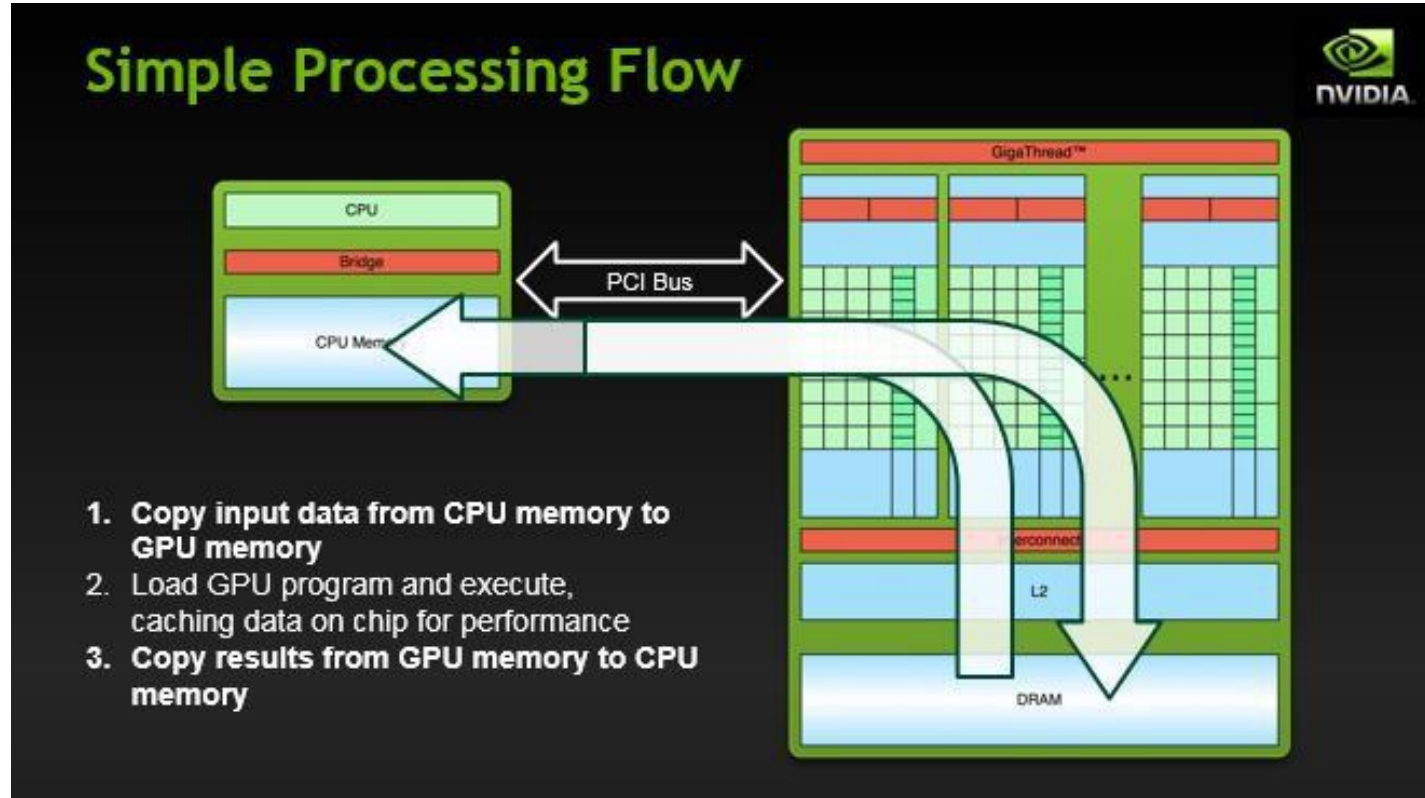
- All device activity issued prior to the item in the default stream must complete before default stream item begins
- All device activity issued after the item in the default stream will wait for the default stream item to finish
- All host threads share the same default stream for legacy behavior
- Consider avoiding use of default stream during complex concurrency scenarios
- Behavior can be modified to convert it to an “ordinary” stream
 - `nvcc --default-stream per-thread ...`
 - Each host thread will get its own “ordinary” default stream

Stream callbacks

- **Allows definition of a host-code function that will be issued into a CUDA stream**
- **Follows stream semantics: function will not be called until stream execution reaches that point**
- **Uses a thread spawned by the GPU driver to perform the callback work**
- **Has limitations: do not use any CUDA runtime API calls (or kernel launches) in the callback**
- **Useful for deferring CPU work until GPU results are ready**

Managed Memory

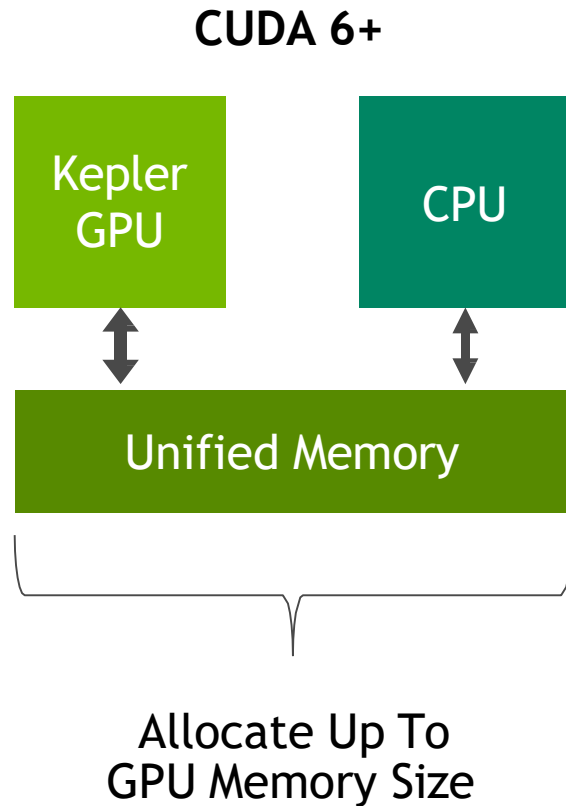
THE CUDA 3-STEP PROCESSING SEQUENCE



->Wouldn't it be nice if we didn't have to do (i.e. write the code for) steps 1 and 3?

Managed Memory

Reduce Developer Effort



Simpler Programming & Memory Model

- Single allocation, single pointer, accessible anywhere
- Eliminate need for *explicit* copy
- Simplifies code porting

Maintain Performance through Data Locality

- Migrate data to accessing processor
- Guarantee global coherence
- Still allows explicit hand tuning

SIMPLIFIED MEMORY MANAGEMENT CODE

CPU Code

```
void sortfile(FILE *fp, int N) {  
    char *data;  
    data = (char *)malloc(N);  
  
    fread(data, 1, N, fp);  
  
    qsort(data, N, 1, compare);  
  
    use_data(data);  
  
    free(data);  
}
```

Ordinary CUDA Code

```
void sortfile(FILE *fp, int N) {  
    char *data, *d_data;  
    data = (char *)malloc(N);  
    cudaMalloc(&d_data, N);  
    fread(data, 1, N, fp);  
    cudaMemcpy(d_data, data, N, ...); // 1  
    qsort<<<...>>>(data, N, 1, compare); // 2  
    cudaMemcpy(data, d_data, N, ...); // 3  
  
    use_data(data);  
    cudaFree(d_data);  
    free(data);  
}
```

SIMPLIFIED MEMORY MANAGEMENT CODE

CPU Code

```
void sortfile(FILE *fp, int N) {  
    char *data;  
    data = (char *)malloc(N);  
  
    fread(data, 1, N, fp);  
  
    qsort(data, N, 1, compare);  
  
    use_data(data);  
  
    free(data);  
}
```

CUDA Code with Unified Memory

```
void sortfile(FILE *fp, int N) {  
    char *data;  
    cudaMallocManaged(&data, N);  
  
    fread(data, 1, N, fp);  
  
    qsort<<<...>>>(data, N, 1, compare);  
    cudaDeviceSynchronize();  
  
    use_data(data);  
  
    cudaFree(data);  
}
```

Copy-compute overlap with managed memory

In particular, with demand-paging

- Follow same pattern, except use `cudaMemPrefetchAsync()` instead of `cudaMemcpyAsync()`
- Stream semantics will guarantee that any needed migrations are performed in proper order
- However, `cudaMemPrefetchAsync()` has more work to do than `cudaMemcpyAsync()` (updating of page tables in CPU and GPU)
- This means the call can take substantially more time to return than an “ordinary” async call – can introduce unexpected gaps in timeline
- Behavior varies for “busy” streams vs. idle streams. Counterintuitively, “busy” streams may result in better throughput

Aside: cudaEvent

- **cudaEvent** is an entity that can be placed as a “marker” in a stream
- A **cudaEvent** is said to be “recorded” when it is issued
- A **cudaEvent** is said to be “completed” when stream execution reaches the point where it was recorded
- **Most common use: timing**

```
cudaEvent_t start, stop;           // cudaEvent has its own type
cudaEventCreate(&start);           // cudaEvent must be created
cudaEventCreate(&stop);            // before use
cudaEventRecord(start);            // “recorded” (issued) into default stream
kernel<<<b, t>>>(...);             // could be any set of CUDA device activity
cudaEventRecord(stop);
cudaEventSynchronize(stop);        // wait for stream execution to reach “stop” event
cudaEventElapsedTime(&float_var, start, stop); // measure kernel duration
```

- **Also useful for arranging complex concurrency scenarios**
- **Event-based timing may give unexpected results for host activity or complex concurrency scenarios**

Multi-GPU – Device Management

- Application can query and select GPUs

```
cudaGetDeviceCount(int *count)
```

```
cudaSetDevice(int device)
```

```
cudaGetDevice(int *device)
```

```
cudaGetDeviceProperties(cudaDeviceProp *prop, int device)
```

- Multiple host threads can share a device

- A single host thread can manage multiple devices

```
cudaSetDevice(i) to select current device
```

```
cudaMemcpyPeerAsync(...) for peer-to-peer copies†
```

Multi-GPU – Streams

- Streams (and cudaEvent) have implicit/automatic *device association*
- Each device also has its own unique default stream
- Kernel launches will fail if issued into a stream not associated with current device
- `cudaStreamWaitEvent()` can synchronize streams belonging to separate devices, `cudaEventQuery()` can test if an event is “complete”
- Simple device concurrency:

```
cudaSetDevice(0);  
cudaStreamCreate(&stream0);           //associated with device 0  
cudaSetDevice(1);  
cudaStreamCreate(&stream1);           //associated with device 1  
Kernel<<<b, t, 0, stream1>>>(...);    // these kernels have the possibility  
cudaSetDevice(0);  
Kernel<<<b, t, 0, stream0>>>(...);    // to execute concurrently
```


Multi-GPU – Device-to-Device data copying

- If system topology supports it, data can be copied directly from one device to another over a fabric (PCIe, or NVLink)
- Device must first be explicitly placed into a peer relationship (“clique”)
- Must enable “peering” for both directions of transfer (if needed)
- Thereafter, memory copies between those two devices will not “stage” through a system memory buffer (GPUDirect P2P transfer)

```
cudaSetDevice(0);  
cudaDeviceCanAccessPeer(&canPeer, 0, 1); // test for 0, 1 peerable  
cudaDeviceEnablePeerAccess(1, 0);        // device 0 sees device 1 as a “peer”  
cudaSetDevice(1);  
cudaDeviceEnablePeerAccess(0, 0);        // device 1 sees device 0 as a “peer”  
cudaMemcpyPeerAsync(dst_ptr, 0, src_ptr, 1, size, stream0); //dev 1 to dev 0 copy  
cudaDeviceDisablePeerAccess(0);          // dev 0 is no longer a peer of dev 1
```

- Limit to the number of peers in your “clique”

Other concurrency scenarios

Host/Device execution concurrency:

```
kernel<<<b, t>>>(...);    // this kernel execution can overlap with  
cpuFunction(...);        // this host code
```

Concurrent kernels:

```
kernel<<<b, t, 0, stream0>>>(...);    // these kernels have the possibility  
kernel<<<b, t, 0, stream1>>>(...);    // to execute concurrently
```

- In practice, concurrent kernel execution on the same device is hard to witness
- Requires kernels with relatively low resource utilization and relatively long execution time
- There are hardware limits to the number of concurrent kernels per device
- Less efficient than saturating the device with a single kernel

Stream priority

- **CUDA streams allow an optional definition of a *priority***
- **This affects execution of concurrent kernels (only).**
- **The GPU block scheduler will attempt to schedule blocks from high priority (stream) kernels before blocks from low priority (stream) kernels**
- **Current implementation only has 2 priorities**
- **Current implementation does not cause preemption of blocks**

```
// 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 available priorities
cudaStream_t st_high, st_low;
cudaStreamCreateWithPriority(&st_high, cudaStreamNonBlocking, priority_high);
cudaStreamCreateWithPriority(&st_low, cudaStreamNonBlocking, priority_low);
```

CUDA Graphs (overview)

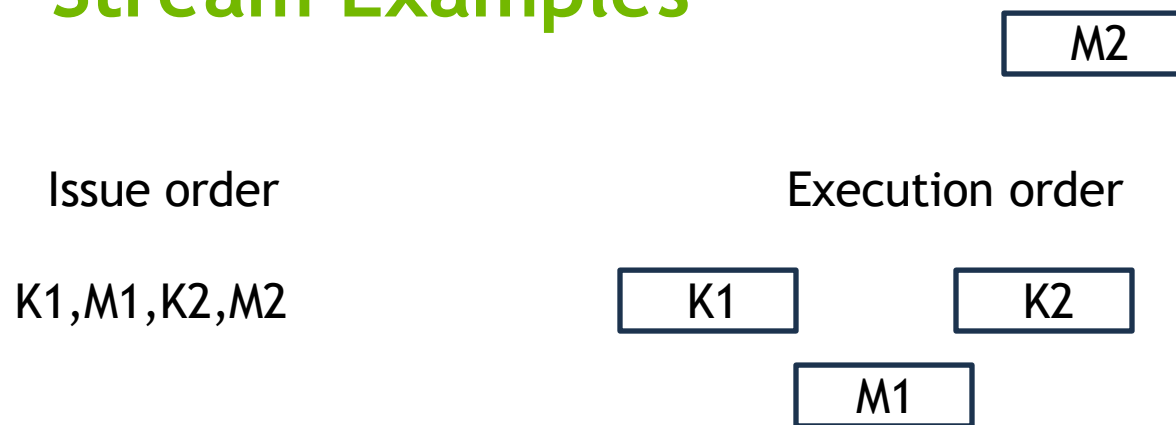
- New feature in CUDA 10
- Allows for the definition of a sequence of stream(s) work (kernels, memory copy operations, callbacks, host functions, graphs)
- Each work item is a *node* in the graph
- Allows for the definition of *dependencies* (e.g. these 3 nodes must finish before this one can begin)
- Dependencies are effectively graph edges
- Once defined, a graph may be executed by launching it into a stream
- Once defined, a graph may be re-used
- Has both a manual definition method and a “capture” method



FURTHER STUDY

- Concurrency with Unified Memory:
 - <https://devblogs.nvidia.com/maximizing-unified-memory-performance-cuda/>
- Programming Guide:
 - <https://docs.nvidia.com/cuda/cuda-c-programming-guide/index.html#asynchronous-concurrent-execution>
- CUDA Sample Codes: concurrentKernels, simpleStreams, asyncAPI, simpleCallbacks, simpleP2P
- Video processing pipeline with callbacks:
 - <https://stackoverflow.com/questions/31186926/multithreading-for-image-processing-at-gpu-using-cuda/31188999#31188999>

Stream Examples



K: kernels
M: memcopy
Number: stream ID