

GPU Teaching Kit

Accelerated Computing



Module 14 – Efficient Host-Device Data Transfer

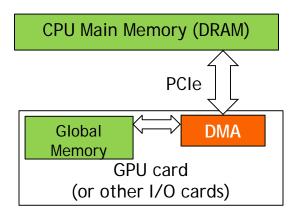
Lecture 14.1 - Pinned Host Memory

Objective

- To learn the important concepts involved in copying (transferring) data between host and device
 - Direct Memory Access
 - Pinned memory

CPU-GPU Data Transfer using DMA

- DMA (Direct Memory Access) hardware is used by cudaMemcpy() for better efficiency
 - Frees CPU for other tasks
 - Hardware unit specialized to transfer a number of bytes requested by OS
 - Between physical memory address space regions (some can be mapped I/O memory locations)
 - Uses system interconnect, typically PCIe in today's systems



Virtual Memory Management

- Modern computers use virtual memory management
 - Many virtual memory spaces mapped into a single physical memory
 - Virtual addresses (pointer values) are translated into physical addresses
- Not all variables and data structures are always in the physical memory
 - Each virtual address space is divided into pages that are mapped into and out of the physical memory
 - Virtual memory pages can be mapped out of the physical memory (page-out) to make room
 - Whether or not a variable is in the physical memory is checked at address translation time

Data Transfer and Virtual Memory

- DMA uses physical addresses
 - When cudaMemcpy() copies an array, it is implemented as one or more DMA transfers
 - Address is translated and page presence checked for the entire source and destination regions at the beginning of each DMA transfer
 - No address translation for the rest of the same DMA transfer so that high efficiency can be achieved
- The OS could accidentally page-out the data that is being read or written by a DMA and page-in another virtual page into the same physical location

Pinned Memory and DMA Data Transfer

- Pinned memory are virtual memory pages that are specially marked so that they cannot be paged out
- Allocated with a special system API function call
- a.k.a. Page Locked Memory, Locked Pages, etc.
- CPU memory that serve as the source or destination of a DMA transfer must be allocated as pinned memory

CUDA data transfer uses pinned memory.

- The DMA used by cudaMemcpy() requires that any source or destination in the host memory is allocated as pinned memory
- If a source or destination of a cudaMemcpy() in the host memory is not allocated in pinned memory, it needs to be first copied to a pinned memory – extra overhead
- cudaMemcpy() is faster if the host memory source or destination is allocated in pinned memory since no extra copy is needed

Allocate/Free Pinned Memory

- cudaHostAlloc(), three parameters
 - Address of pointer to the allocated memory
 - Size of the allocated memory in bytes
 - Option use cudaHostAllocDefault for now
- cudaFreeHost(), one parameter
 - Pointer to the memory to be freed

Using Pinned Memory in CUDA

- Use the allocated pinned memory and its pointer the same way as those returned by malloc();
- The only difference is that the allocated memory cannot be paged by the OS
- The cudaMemcpy() function should be about 2X faster with pinned memory
- Pinned memory is a limited resource
 - over-subscription can have serious consequences

Putting It Together - Vector Addition Host Code Example

```
int main()
{
   float *h_A, *h_B, *h_C;
...
   cudaHostAlloc((void **) &h_A, N* sizeof(float),
      cudaHostAllocDefault);
   cudaHostAlloc((void **) &h_B, N* sizeof(float),
      cudaHostAllocDefault);
   cudaHostAlloc((void **) &h_C, N* sizeof(float),
      cudaHostAllocDefault);
...
   // cudaMemcpy() runs 2X faster
}
```



GPU Teaching Kit

Accelerated Computing





The GPU Teaching Kit is licensed by NVIDIA and the University of Illinois under the <u>Creative Commons Attribution-NonCommercial 4.0 International License.</u>



GPU Teaching Kit

Accelerated Computing



Module 14 – Efficient Host-Device Data Transfer

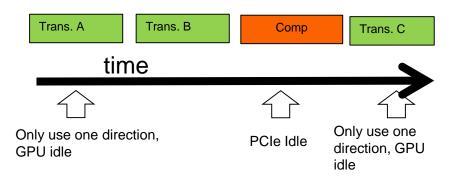
Lecture 14.2 - Task Parallelism in CUDA

Objective

- To learn task parallelism in CUDA
 - CUDA Streams

Serialized Data Transfer and Computation

 So far, the way we use cudaMemcpy serializes data transfer and GPU computation for VecAddKernel()



Device Overlap

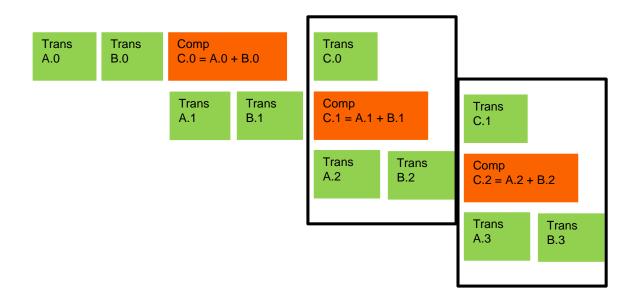
- Some CUDA devices support device overlap
 - Simultaneously execute a kernel while copying data between device and host memory

```
int dev_count;
cudaDeviceProp prop;

cudaGetDeviceCount( &dev_count);
for (int i = 0; i < dev_count; i++) {
   cudaGetDeviceProperties(&prop, i);
   if (prop.deviceOverlap) ...</pre>
```

Ideal, Pipelined Timing

- Divide large vectors into segments
- Overlap transfer and compute of adjacent segments



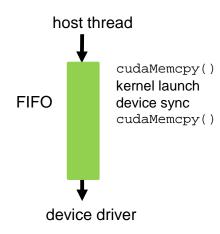
CUDA Streams

- CUDA supports parallel execution of kernels and cudaMemcpy() with "Streams"
- Each stream is a queue of operations (kernel launches and cudaMemcpy() calls)
- Operations (tasks) in different streams can go in parallel
 "Task parallelism"

□ NVIDIA

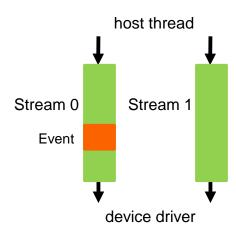
Streams

- Requests made from the host code are put into First-In-First-Out queues
 - Queues are read and processed asynchronously by the driver and device
 - Driver ensures that commands in a queue are processed in sequence. E.g.,
 Memory copies end before kernel launch, etc.

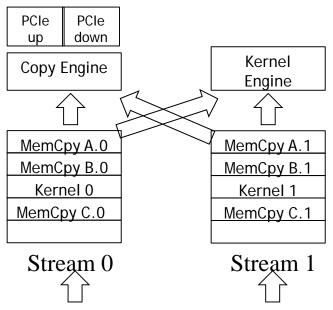


Streams cont.

- To allow concurrent copying and kernel execution, use multiple queues, called "streams"
 - CUDA "events" allow the host thread to query and synchronize with individual queues (i.e. streams).



Conceptual View of Streams



Operations (Kernel launches, cudaMemcpy() calls)

● INVIDIA



GPU Teaching Kit

Accelerated Computing





The GPU Teaching Kit is licensed by NVIDIA and the University of Illinois under the <u>Creative Commons Attribution-NonCommercial 4.0 International License.</u>



GPU Teaching Kit

Accelerated Computing



Module 14 – Efficient Host-Device Data Transfer

Lecture 14.3 - Overlapping Data Transfer with Computation

Objective

- To learn how to overlap data transfer with computation
 - Asynchronous data transfer in CUDA
 - Practical limitations of CUDA streams

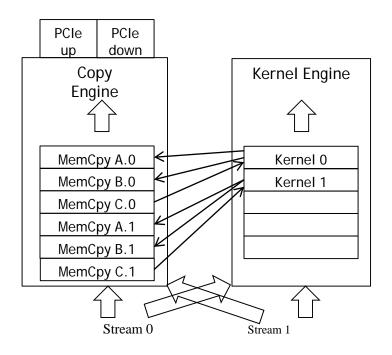
Simple Multi-Stream Host Code

```
cudaStream_t stream0, stream1;
cudaStreamCreate(&stream0);
cudaStreamCreate(&stream1);
float *d_A0, *d_B0, *d_C0; // device memory for stream 0
float *d_A1, *d_B1, *d_C1; // device memory for stream 1
// cudaMalloc() calls for d_A0, d_B0, d_C0, d_A1, d_B1, d_C1 go
here
```

Simple Multi-Stream Host Code (Cont.)

```
for (int i=0; i<n; i+=SegSize*2) {
    cudaMemcpyAsync(d_A0, h_A+i, SegSize*sizeof(float),..., stream0);
    cudaMemcpyAsync(d_B0, h_B+i, SegSize*sizeof(float),..., stream0);
    vecAdd<<<SegSize/256, 256, 0, stream0>>>(d_A0, d_B0,...);
    cudaMemcpyAsync(h_C+i, d_C0, SegSize*sizeof(float),..., stream0);
    cudaMemcpyAsync(d_A1, h_A+i+SegSize, SegSize*sizeof(float),..., stream1);
    cudaMemcpyAsync(d_B1, h_B+i+SegSize, SegSize*sizeof(float),..., stream1);
    vecAdd<<<SegSize/256, 256, 0, stream1>>>(d_A1, d_B1, ...);
    cudaMemcpyAsync(d_C1, h_C+i+SegSize, SegSize*sizeof(float),..., stream1);
}
```

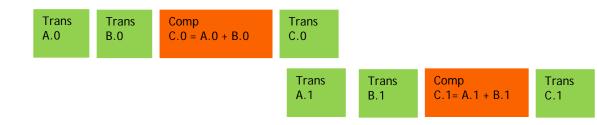
A View Closer to Reality in Previous GPUs



Operations (Kernel launches, cudaMemcpy() calls)

Not quite the overlap we want in some GPUs

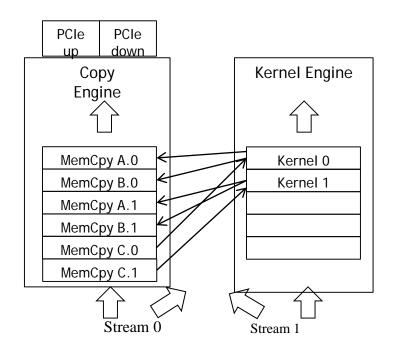
- C.0 blocks A.1 and B.1 in the copy engine queue



Better Multi-Stream Host Code

```
for (int i=0; i<n; i+=SegSize*2) {
    cudaMemcpyAsync(d_A0, h_A+i, SegSize*sizeof(float),..., stream0);
    cudaMemcpyAsync(d_B0, h_B+i, SegSize*sizeof(float),..., stream0);
    cudaMemcpyAsync(d_A1, h_A+i+SegSize, SegSize*sizeof(float),..., stream1);
    cudaMemcpyAsync(d_B1, h_B+i+SegSize, SegSize*sizeof(float),..., stream1);
    vecAdd<<<SegSize/256, 256, 0, stream0>>>(d_A0, d_B0, ...);
    vecAdd<<<SegSize/256, 256, 0, stream1>>>(d_A1, d_B1, ...);
    cudaMemcpyAsync(h_C+i, d_C0, SegSize*sizeof(float),..., stream0);
    cudaMemcpyAsync(h_C+i+SegSize, d_C1, SegSize*sizeof(float),..., stream1);
}
```

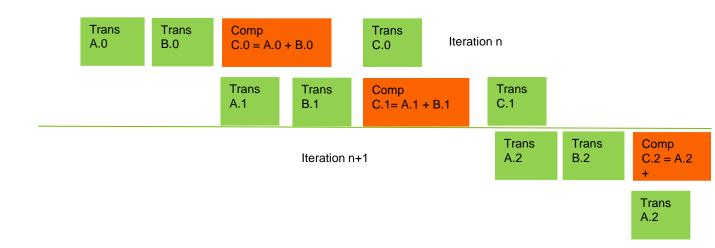
C.0 no longer blocks A.1 and B.1



Operations (Kernel launches, cudaMemcpy() calls)

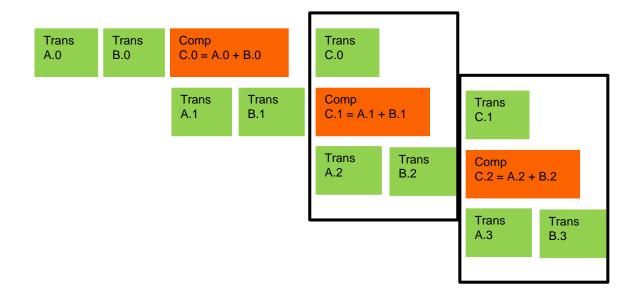
Better, not quite the best overlap

C.1 blocks next iteration A.0 and B.0 in the copy engine queue



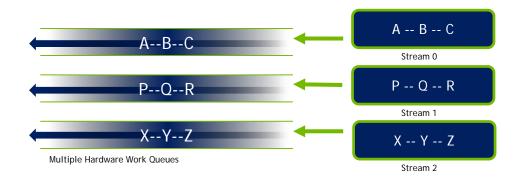
Ideal, Pipelined Timing

 Will need at least three buffers for each original A, B, and C, code is more complicated



Hyper Queues

- Provide multiple queues for each engine
- Allow more concurrency by allowing some streams to make progress for an engine while others are blocked



Wait until all tasks have completed

- cudaStreamSynchronize(stream_id)
 - Used in host code
 - Takes one parameter stream identifier
 - Wait until all tasks in a stream have completed
 - E.g., cudaStreamSynchronize(stream0)in host code ensures that all tasks in the queues of stream0 have completed

- This is different from cudaDeviceSynchronize()
 - Also used in host code
 - No parameter
 - cudaDeviceSynchronize() waits until all tasks in all streams have completed for the current device



GPU Teaching Kit

Accelerated Computing





The GPU Teaching Kit is licensed by NVIDIA and the University of Illinois under the <u>Creative Commons Attribution-NonCommercial 4.0 International License.</u>

GPU Teaching Kit

Accelerated Computing

Module 14 – Efficient Host-Device Data Transfer Lecture 14.4 – CUDA Unified Memory



Objective

- To learn the important concepts involved in an efficient use of CUDA Unified Memory
 - Prefetching
 - Memory Advisor



Data Prefetching in CUDA Unified Memory

- Main purpose being to avoid page faults
- Establishes data locality, providing a mechanism to improve the performance of the application
- Used to migrate data to a device or the host and map page tables onto the processor before it begins using data
- Most useful when the data is accessed from a single processor

Data Prefetching CUDA API

- cudaMemPrefetchAsync()

- Four parameters
 - Unified Memory Address of the memory region to prefetch
 - Size of the region to prefetch in terms of bytes
 - Destination processor
 - CUDA stream

- Prefetching is an asynchronous operation with respect to the device, however the call may not be fully asynchronous with respect to the host.
- The destination processor must be a valid device ID or *cudaCpuDeviceId*, the later will prefetch the memory to the host.
- If the prefetch processor is a GPU, the device property cudaDevAttrConcurrentManagedAccess Must be nonzero.





Putting it all together

```
void function(int * data, cudaStream_t stream) {
  // data must've been allocated with cudaMallocManaged( (void**) &data, N);
  init(data, N);
                                                                            // Init data on the host
  cudaMemPrefetchAsync(data, N * sizeof(int), myGpuld, stream);
                                                                            // Prefetch to the device
  kernel<<<..., stream>>>(data, ...);
                                                                            // Execute on the device
  cudaMemPrefetchAsync(data, N * sizeof(int), cudaCpuDeviceId, stream); // Prefetch to the host
  cudaStreamSynchronize(stream);
  hostFunction(data, N);
```



CUDA Unified Memory - Memory Advisor

- Hints that can be provided to the driver on how data will be used during runtime
- One example of when we can give an advice is when data will be accessed from multiple processors at the same time



Memory Advisor CUDA API

- cudaMemAdvise()
 - Four parameters
 - Unified Memory Address of the memory region to advise
 - Size of the region to advise in terms of bytes
 - Memory advise
 - Destination processor

- The destination processor must be a valid device ID or cudaCpuDeviceId.
- Available memory hints are:
 - cudaMemAdviseSetReadMostly
 - cudaMemAdviseSetPreferredLocation
 - cudaMemAdviseSetAccessedBy

To unset the advice:

- cudaMemAdviseUnsetReadMostly
- cudaMemAdviseUnsetPreferredLocation
- cudaMemAdviseUnsetAccessedBy





Memory Advisor CUDA API

cudaMemAdviseSetReadMostly:

- This tells the UM driver that the memory region is mostly for reading purposes and occasionally writing.
- All read accesses from a processor will create a read only copy to be accessed.
- The device argument is ignored.
- When used in conjunction with cudaMemPrefetchAsync() a read only copy will be created in the specified device.

– cudaMemAdviseSetPreferredLocation:

- This tells the UM driver the preferred location of the data.
- However this does not cause immediate data migration to the location, it only guides the migration policy for the UM driver.
- If the destination processor is a GPU, then that GPU needs a nonzero value for the device flag cudaDevAttrConcurrentManagedAccess.





Memory Advisor CUDA API

– cudaMemAdviseSetAccessedBy:

- This tell the UM driver that the data will be accessed by the specified processor.
- This advice does not cause immediate data migration to the location, it only causes data to always be mapped in the specified processor's pages.
- It is useful to avoid page faulting, like when in a multi-GPU system one device wants to access another GPU's memory but migrating the data may be more expensive than just reading it through the PCIE link.





Putting it all together

```
void function(int * data, cudaStream_t stream) {
  // data must be addressable by the Unified Memory driver.
                   // Init data on the host
  init(data, N);
  cudaMemAdvise(data, N * sizeof(int), cudaMemAdviseSetReadMostly, 0); // Set the advice for read only.
  cudaMemPrefetchAsync(data, N * sizeof(int), myGpuld1, stream1);
                                                                               // Prefetch to the 1st device.
  cudaMemPrefetchAsync(data, N * sizeof(int), myGpuld2, stream2);
                                                                               // Prefetch to the 2nd device.
  cudaSetDevice(myGpuld1);
                                                                     // Execute read only operations
  kernel<<<..., stream>>>(data, ...);
                                                                     // on the 1st device.
  cudaSetDevice(myGpuld2);
                                                                     // Execute read only operations
  kernel<<<..., stream>>>(data, ...);
                                                                     // on the 2nd device.
```



GPU Teaching Kit

Accelerated Computing

The GPU Teaching Kit is licensed by NVIDIA under the <u>Creative Commons</u> Attribution-NonCommercial 4.0 International License.

