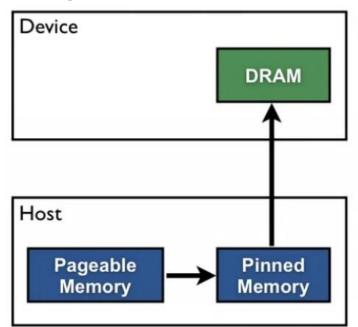
# **Parallel Programming CUDA Streams** Phạm Trọng Nghĩa ptnghia@fit.hcmus.edu.vn

# Host device data transfer

# **Memory Allocation Types**

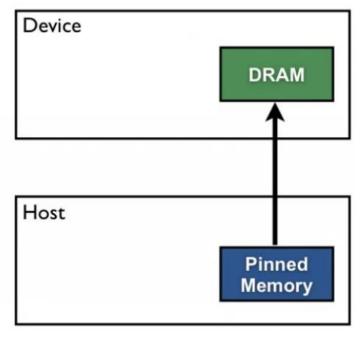
- Device memory (cannot be paged)
- (Host) Pageable memory
- (Host) Pinned memory
- (Both) Mapped memory
- (Both) Unified memory

#### **Pageable Data Transfer**



#### What we learn

#### **Pinned Data Transfer**

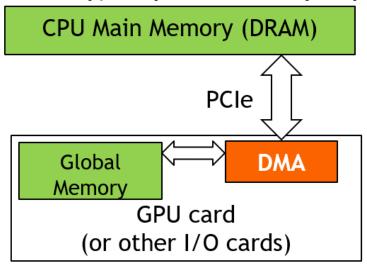


# Virtual Memory Management

- 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

# **Memory Allocation Types**

- Pagable memory is transferred using the host CPU (memory Map I/O)
- Pinned memory is transferred using the DMA engines
  - Frees the CPU for asynchronous execution
  - Achieves a higher percent of peak bandwidth
- cudaMemcpy() use DMA (Direct Memory Access) hardware
  - Hardware unit specialized to transfer a number of bytes requested by OS
  - Between physical memory address space regions
  - Uses system interconnect, typically PCIe in today's systems



## **Data Transfer and Virtual Memory**

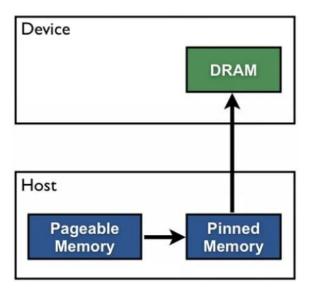
- DMA uses physical addresses
  - When cudaMemcpy() copies an array, it is implemented as one or more DMA transfers
  - Address is translated and page presence checked for the entire source and destination regions at the beginning of each DMA transfer
  - No address translation for the rest of the same 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 & 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

# Pageable memory

- The memory allocated in host is by default pageable memory (malloc)
- To transfer this data to the device, the CUDA run time copies this memory to a temporary pinned memory and then transfers to the device memory.
- There are two memory transfers → Slow



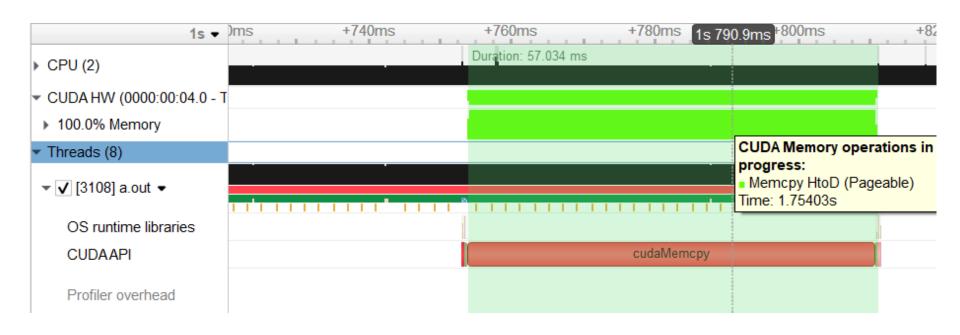
# Pageable memory - Usage

```
int* h_in = (int*)malloc(nBytes);
// Init data for h_in ...
int* d_in;
cudaMalloc(&d_in, nBytes);

// Copy data to device memories
cudaMemcpy(d_in, in, nBytes, cudaMemcpyHostToDevice));

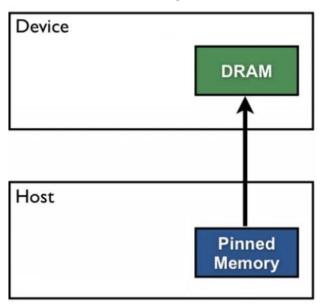
cudaFree(d_in);
free(in);
```

# Pageable memory - Usage



# Pinned memory

- The data can be initialized directly in the host pinned memory.
- Avoid two data transfers as in pageable memory.
- Make the process faster but at the cost of host performance.
  - When data is initialized in the *pinned memory*, the memory availability for host processing is reduced



# Pinned memory

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

# Pinned memory - Usage

```
int* h_in;
int* d_in
cudaMallocHost(&h_in, nBytes);
// Init data for h_in ...

cudaMalloc(&d_in, nBytes);

// Copy data to device memories
cudaMemcpy(d_in1, in1, nBytes, cudaMemcpyHostToDevice);
//...
cudaFree(d_in);
cudaFreeHost(h_in);
```

# Pinned memory - Usage



# Mapped memory

- Mapped memory (zero-copy memory): pinned memory that is mapped into the device address space.
- Both host and device have direct access to this memory.

#### Pros:

- Can leverage host memory when there is insufficient device memory.
- Can avoid explicit data transfers between host and device.
- Improves PCIe transfer rates

#### Cons

 Transfer will happen during execution which will increase the processing time considerably

# Mapped memory - Usage

Host allocation:

```
int* h_a2, * h_b2, * h_c2;
cudaHostAlloc((int**)&h_a2, nBytes, cudaHostAllocMapped);
cudaHostAlloc((int**)&h_b2, nBytes, cudaHostAllocMapped);
cudaHostAlloc((int**)&h_c2, nBytes, cudaHostAllocMapped);
```

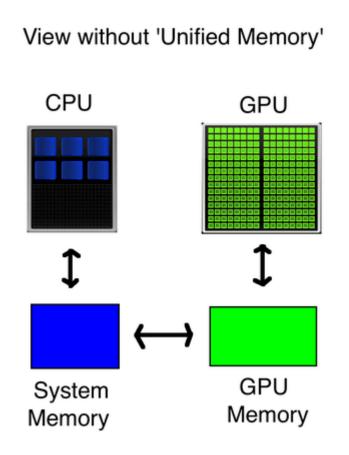
Device allocation:

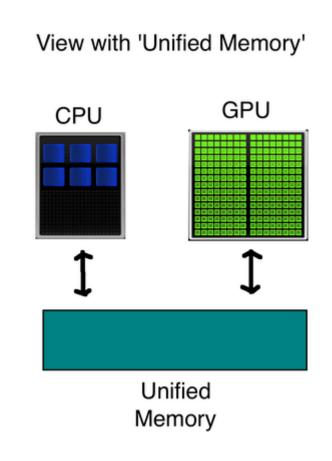
```
int* d_a2, * d_b2, * d_c2;
cudaHostGetDevicePointer(&d_a2, h_a2, 0);
cudaHostGetDevicePointer(&d_b2, h_b2, 0);
cudaHostGetDevicePointer(&d_c2, h_c2, 0);
```

 cudaHostGetDevicePointer: Passes back the device pointer corresponding to the mapped, pinned host buffer allocated by cudaHostAlloc()

# **Unified memory**

More general than Mapped memory





# **Unified memory**

- Is a single memory address space accessible both from the host and from the device.
- The hardware/software handles automatically the data migration between the host and the device maintaining consistency between them.

#### Pros:

- No explicit allocation and recovery of memory for device needed.
   This reduces programming complexity.
- Enabling larger arrays than the device memory size.

#### Cons

Adds additional instructions under the hood for memory management

# **Unified memory - Usage**

Only need 1 initialization

```
int *a, *b, *c;
cudaMallocManaged((int **)&a, nBytes);
cudaMallocManaged((int **)&b, nBytes);
cudaMallocManaged((int **)&c, nBytes);
```

- cudaMallocManaged()
  - Allocates an object in the Unified Memory address space.
  - Address of a pointer to the allocated object
  - Size of the allocated object in terms of bytes
- cudaFree()
  - Frees object from unified memory.
- cudaMemcpy()
  - · Copy data between different arrays, regardless of position
  - Direction: cudaMemcpyDefault

# Comparision

- Runing Matrix addition with #rows = 4096, #cols = 8192
- Run on Tesla T4 (C.C 7.5)

Memory	Total run time
Pageable	152.19 ms
Pinned	38.22 ms
Mapped	22.00 ms
Unified	122.11 ms

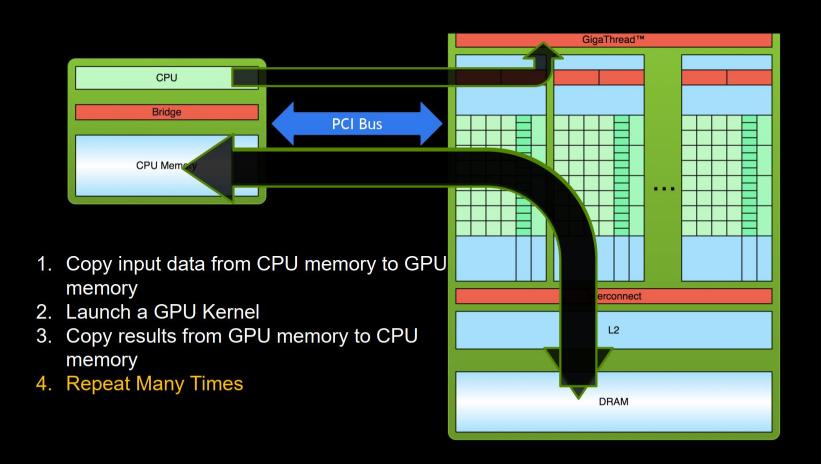
**Note**: these numbers will change depend on hardware

# **CUDA STREAM**

#### Introduction

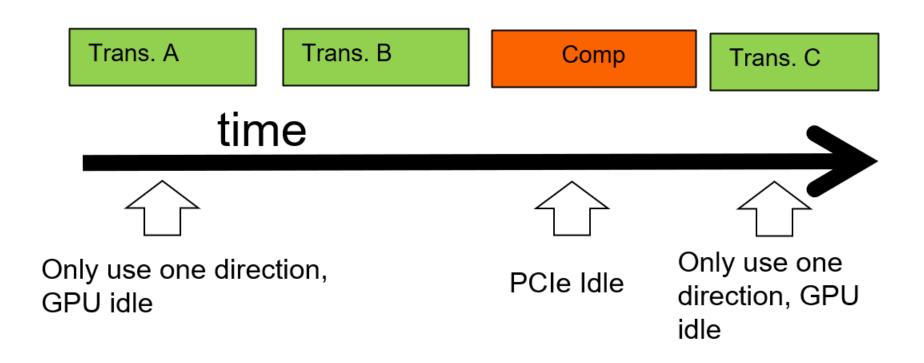
- Optimization: try to make full use of hardware resources, don't let any of them idle
- So far, we have discussed about optimization limited to the scope of a kernel
  - Need enough blocks to utilize SMs
  - In each SM, need enough independent instructions (coming from one warp or from different warps) to utilize execution pipelines, hide latency
  - Minimize warp divergence
- Today, we will discuss about optimization in a bigger scope:
   outside a kernel

# Simple processing Flow

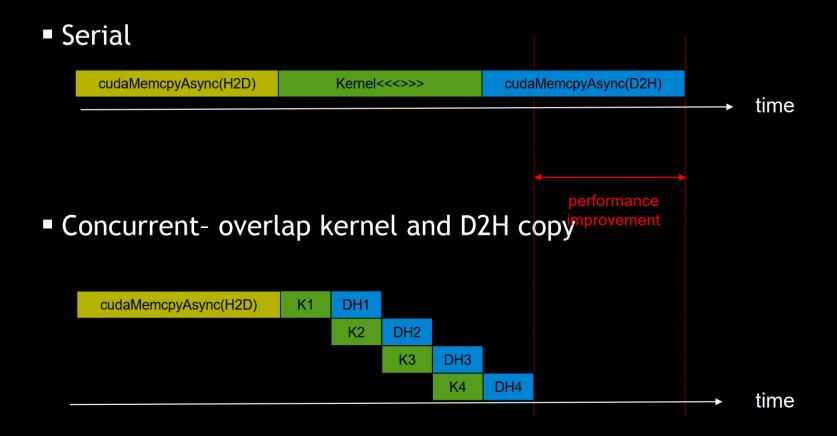


# Simple processing Flow

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



# **Concurrency Through Pipelining**



Source: Justin Luitjens, CUDA Streams, GTC2014

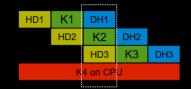
# Concurrency Through Pipelining

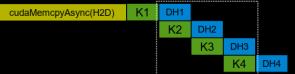
Serial (1x)

cudaMemcpyAsync(H2D) Kernel <<< >>> cudaMemcpyAsync(D2H)

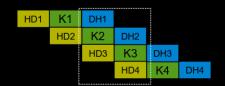
2-way concurrency (up to 2x)

4-way concurrency (3x+)

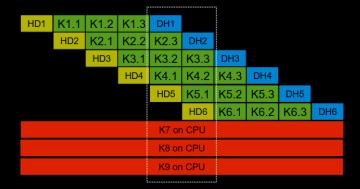




■ 3-way concurrency (up to 3x)



4+ way concurrency



#### Overlap tasks

 With most current devices, in the extreme, we can overlap:

```
many host computations (if utilize CPU cores)

and many device computations (kernels)

and one H2D

and one D2H
```

- Basic conditions to overlap tasks:
  - These tasks are independent of each other
  - There are enough hardware resources for these tasks

#### In CUDA, how to overlap tasks?

When host calls a CUDA command, there are 2 possible situations:

 Synchronous: host sends this command to a device queue and waits until it finishes

E.g, cudaMemcpy

 Asynchronous: host sends this command to a device queue and continues to do other works without waiting this command to finish

E.g., host calls a kernel



By default, we can overlap a host computation and a device computation

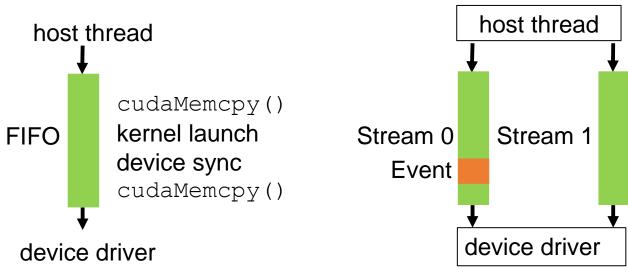
How to overlap other tasks (e.g., a kernel with another kernel)?

#### In CUDA, how to overlap tasks?

- A CUDA stream is a task queue of device Host sends device tasks to this queue
- Tasks in the same stream will be executed by device sequentially in FIFO order
- Tasks in different streams will have no order with each other and can overlap with each other

Driver ensures that commands in a queue are processed

in sequence



#### Stream CUDA commands

Create stream

```
cudaStream_t stream;
cudaStreamCreate(&stream);
```

Destroy stream

```
cudaStreamDestroy(stream);
```

- Send tasks to stream

#### Default stream (stream 0 / NULL stream)

- By default, tasks will be sent to stream 0
- Note: stream 0 synchronizes with other streams

E.g., host sends tasks (T) to streams (S) in order T0-S0, T-S1, T-S2, T1-S0, then in device:

- First, execute T0-S0
- After finishing T0-S0, execute T-S1, T-S2 (T-S1 and T-S2 can overlap)
- After finishing T-S1 and T-S2, execute T1-S0
- To overlap
  - Option 1: replace stream 0 by stream non-0
  - Option 2: create stream non-0 as follows cudaStreamCreateWithFlags(&stream,

cudaStreamNonBlocking)

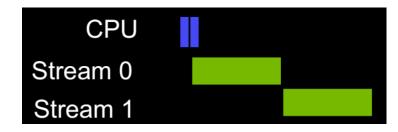
# **Example: overlap kernels**

- Assume a kernel foo only utilizes 50% of device resource
- Use stream 0

```
foo<<<blocks, threads>>>();
foo<<<blocks, threads>>>();
```



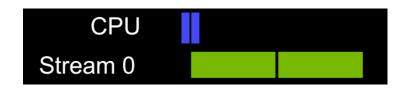
Use stream 0 and stream non-0



# **Example: overlap kernels**

- Assume a kernel foo only utilizes 50% of device resource
- Use stream 0

```
foo<<<blocks, threads>>>();
foo<<<blocks, threads>>>();
```



Use stream 0 and stream non-0

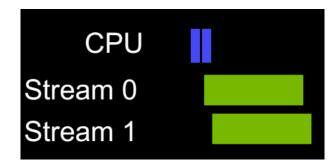
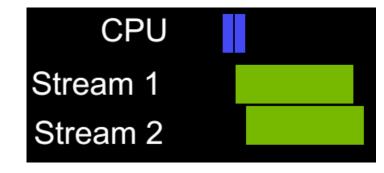


Image source: Justin Luitjens, CUDA Streams, GTC2014

# **Example: overlap kernels**

- Assume a kernel foo only utilizes 50% of device resource
- Use stream non-0



# Example: overlap data transfer with other tasks

#### Example 1

```
cudaMemcpy(...);
foo<<<...>>>();
```

# CPU Stream 0

#### Example 2

```
cudaMemcpyAsync(..., stream1);
```

foo<</p>
foo
stream1>>>():

```
CPU
Stream 1
```

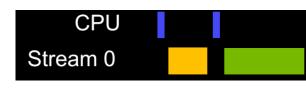
```
Need to pin ♣ host memory: replace malloc by cudaMallocHost (and free by cudaFreeHost)
```

Why? In order for host to continue to do other works and device hardware to transfer data, the physical memory storing data in host must be kept intact – must be pinned; otherwise, data stored in the physical memory of host can be changed by OS while device is transferring data (because of <u>virtual memory mechanism</u> in host)  $\odot$ 

# Example: overlap data transfer with other tasks

#### Example 1

```
cudaMemcpy(...);
foo<<<...>>>();
```



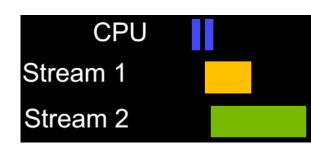
#### Example 2

```
cudaMemcpyAsync(..., stream1);
foo<<<..., stream1>>>();
```



#### Example 3

```
cudaMemcpyAsync(..., stream1);
foo<<<..., stream2>>>();
```

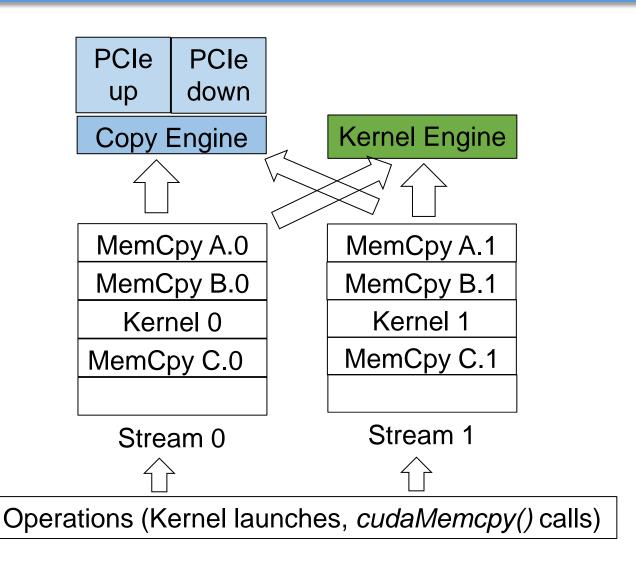


## **Device Overlap**

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

- RTX 3050 Laptop GPU: 1
  - Can only transfer 1 direction at one time.
- Tesla T4 (Colab): 3
  - H2D, D2H, NVLink (With 1 other GPU)
- Volta V100-32GB GPU: 6
  - H2D, D2H, 4 NVLink (With 4 other GPU)

# **Conceptual View of Streams**



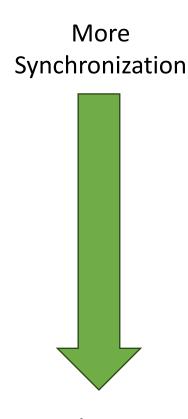
# **Concurrent memory copies**

- cudaMemcpy(...)
  - Places transfer into default stream
  - Synchronous: Must complete prior to returning
- cudaMemcpyAsync(..., &stream)
  - Places transfer into stream and returns immediately
- To achieve concurrency
  - Transfers must be in a non-default stream
  - Must use async copies
  - 1 transfer per direction at a time
  - Memory on the host must be pinned

# **Synchronization**

When we let tasks run asynchronously, we will need to synchronize at some point

- Synchronize everything
  - cudaDeviceSynchronize()
  - Blocks host until all issued CUDA calls are complete
- Synchronize host w.r.t. a specific stream
  - cudaStreamSynchronize(stream)
  - Blocks host until all issued CUDA calls in stream are complete
- Synchronize host or devices using events



Less Synchronization

# **Synchronization**

#### Synchronize host with device

```
cudaDeviceSynchronize();
```

#### Synchronize host with a stream

- cudaStreamSynchronize(stream);
- cudaStreamQuery(stream);
  - Host doesn't have to wait
  - Return: cudaSuccess if all tasks in stream are finished;
     cudaErrorNotReady otherwise

#### **CUDA EVENTS**

- Provide a mechanism to signal when operations have occurred in a stream
  - Useful for profiling and synchronization
- Events have a boolean state:
  - Occurred
  - Not Occurred
  - Important: Default state = occurred

# **Synchronization**

#### Synchronize host with a point in a stream: use event

Create event

```
cudaEvent_t event;
cudaEventCreate(&event);
```

Send event to stream

```
cudaEventRecord(event, stream);
```

- Set the event state to not occurred
- Event state is set to occurred when it reaches the front of the stream
- Synchronize host with event
  - cudaEventSynchronize(event);
  - cudaEventQuery(event);//Similar to cudaStreamQuery
- Destroy event

```
cudaEventDestroy(event);
```

# **Synchronization**

#### Synchronize streams with each other

cudaStreamWaitEvent(stream, event)

- stream waits event (of another stream) to happen, only then it continues to do tasks enqueued to stream after this command
- Host doesn't have to wait



# THE END

#### Reference

- [1] Wen-Mei, W. Hwu, David B. Kirk, and Izzat El Hajj. Programming Massively Parallel Processors: A Hands-on Approach. Morgan Kaufmann, 2022
- [2] Cheng John, Max Grossman, and Ty McKercher. *Professional Cuda C Programming*. John Wiley & Sons, 2014
- [3] Illinois-NVIDIA GPU Teaching Kit
- [4] Cuda Streamsbest Practices And Common Pitfalls, Justin Luitjens -NVIDIA