KAIST

# Top-Down CUDA Overview

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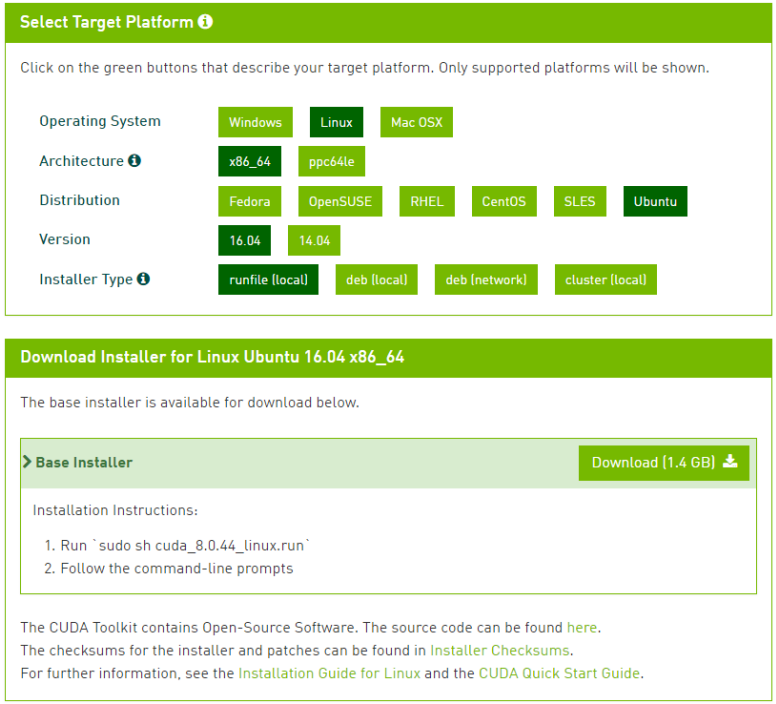
# CUDA Installation for Ubuntu – 1

- Install dependencies
  - `sudo apt-get install gcc make`
- Visit https://developer.nvidia.com/cuda-downloads and download a proper runfile (local)
  - The runfile name is like `cuda_x.x.xx_linux.run`
- Install NVIDIA driver and CUDA toolkit
  - Run `chmod u+x cuda_x.x.xx_linux.run`
  - Run `sudo ./cuda_x.x.xx_linux.run`
  - **Accept** the EULA
  - Install graphics driver: **y**
  - Install OpenGL libraries: **n** if you are not sure
  - Run nvidia-xconfig: **n** for the best GPGPU performance
  - Install CUDA toolkit: **y**
  - Enter toolkit location: type enter (follow the default)
  - Install a symbolic link: **y**
  - Install CUDA samples: **y** if you need sample codes



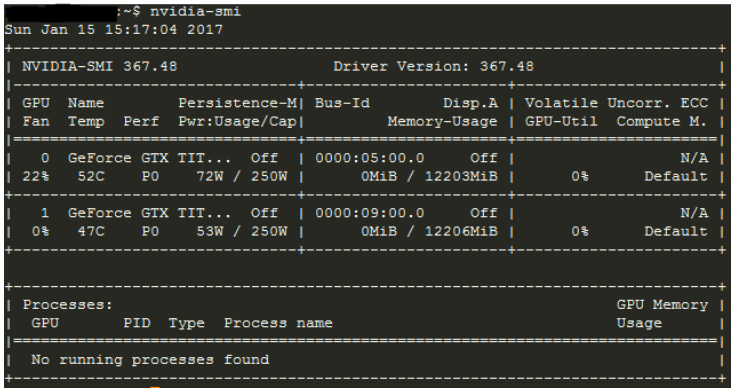

- If the installation succeeds, go to the next slide
- If the installation fails, check logs in `/var/log/nvidia-installer.log`
  - `ERROR: Unable to load the kernel module 'nvidia.ko'`
    → Make sure that secure boot mode is disabled from BIOS. Disable it and try again.

# CUDA Installation for Ubuntu – 2

- If you are installing for all users (recommended)
  - Run `sudo vi /etc/environment`
  - Add `/usr/local/cuda/bin` in `PATH`
  - Add `LD_LIBRARY_PATH=/usr/local/cuda/lib64`
  - Save the file and run `source /etc/environment`
  - Example of `/etc/environment`

```
PATH="/usr/local/sbin:/usr/local/bin:/usr/sbin:/usr/bin:/sbin:/bin:/usr/games:/usr/local/games:/usr/local/cuda/bin"
LD_LIBRARY_PATH=/usr/local/cuda/lib64
```

- If you are installing for your account only (not recommended)
  - Run `vi ~/.bashrc` and at the end of the file,
  - Add `export PATH="$PATH:/usr/loca/cuda/bin"`
  - Add `export LD_LIBRARY_PATH=/usr/local/cuda/lib64`
  - Save the file and run `source ~/.bashrc`




- Done ! (some CUDA applications may require reboot)

- If some problems occur, check whether the driver module is loaded
  - Run `nvidia-smi` and check whether it shows GPU info as the picture
  - `modprobe: FATAL: Module nvidia not found`
    → You may have enabled secure boot after the installation.
    Disable secure boot from BIOS and re-install the *graphics driver only again* via `sudo ./cuda_x.x.xx_linux.run`
  - Running NVIDIA samples sometimes fix issues (1_Utilities/deviceQuery/)

# Heterogeneous Computing – Host and Device

- CPU operates as the *Host* of every NVIDIA GPU *Devices*
- *CUDA* code consists of Host code and Device code
  - *Host* code controls memory and thread execution of a *Device*
  - *Device* code (or *CUDA kernel*) defines operations of GPU threads

**Host (CPU & RAM)**

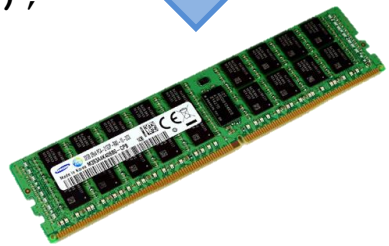

**PCI Express**
**PCIe 3.0 x16: ~16GB/s**

**Device (GPU)**

**Host Code**

```
…
cudaMalloc(…);
cudaMemcpy(…H2D…);
kernel_add<<<…>>>(…);
cudaMemcpy(…D2H…);
cudaFree(…);
…
```

**Memory Bus**
**Intel i7-6950X: ~53GB/s**
**Intel Xeon E5-2697 v4: ~77GB/s**

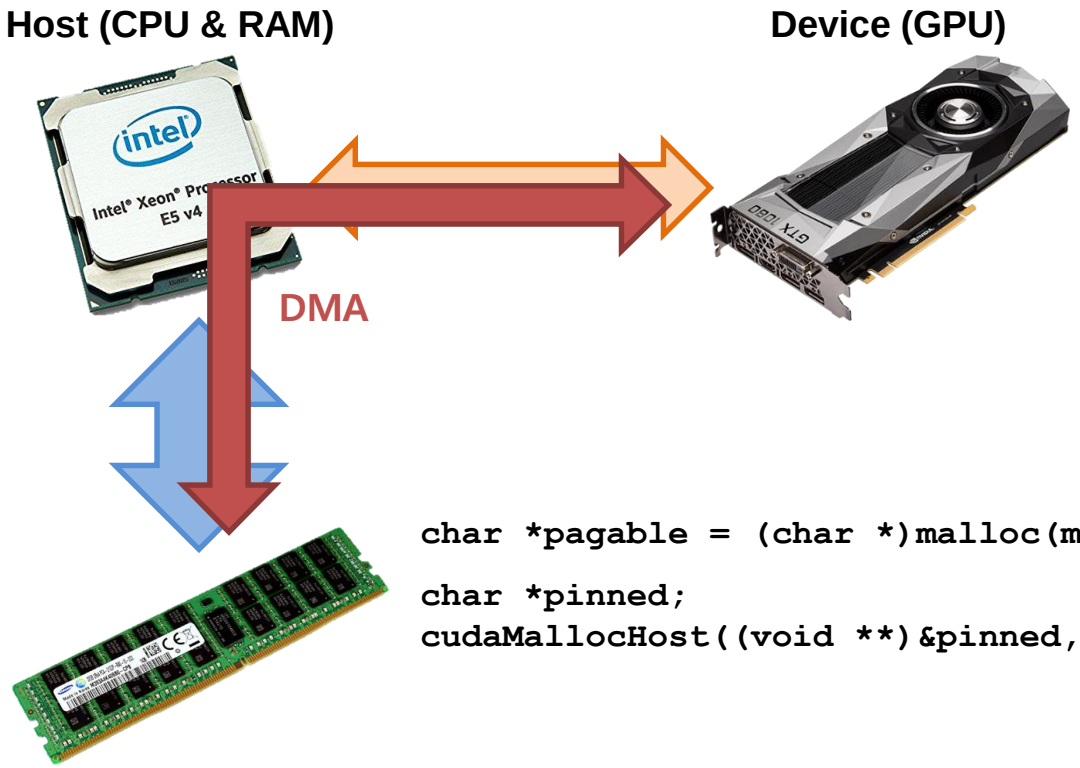


**Device Code (CUDA Kernel)**

```
__global__ void
kernel_add(…)
{
    …
}
```

# Heterogeneous Computing – Pinned Memory

- *Pinned (page-locked) memory* is transferred via DMA
  - Frees CPU to work simultaneously during the memory copy
  - Achieves higher bandwidth than pagable memory copy
- Use `cudaMallocHost()` to allocate pinned host memory

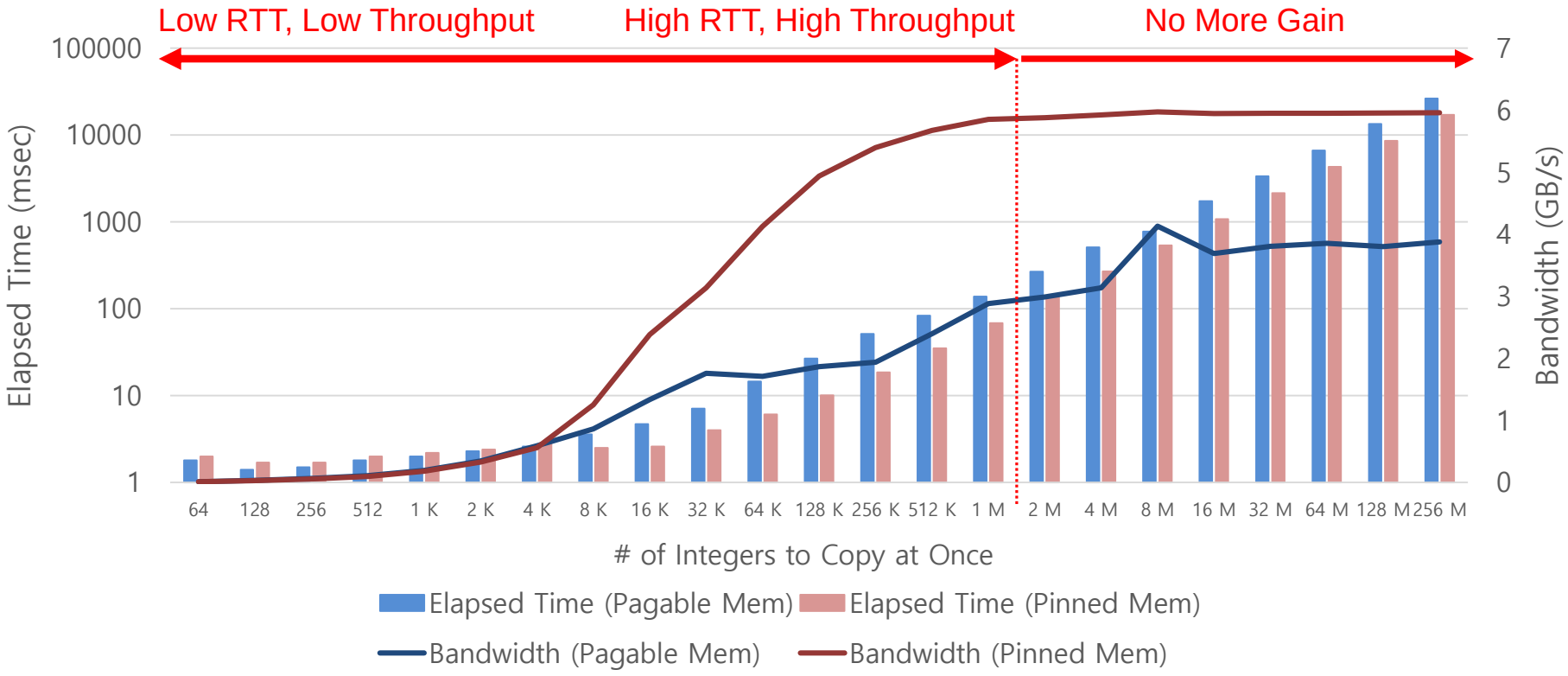



```
char *pagable = (char *)malloc(memSize);

char *pinned;
cudaMallocHost((void **)&pinned, memSize));
```

# Example: Simple Memory Copy

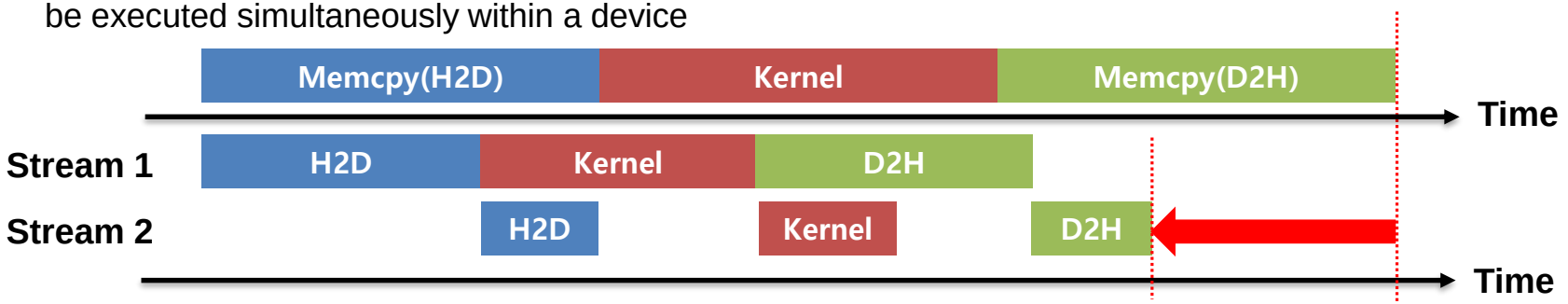
- Run `make simple_copy` to compile `src/simple_copy/main.cu`
- Run `./simple_copy 64` to copy 64 integers to GPU, launch a null kernel, and copy back to RAM
- The code executes these `nloop=100` times to calculate stable memcpy bandwidth
- Check the elapsed time and bandwidth while increasing the number of integers to copy at once
- Check the difference between using pagable memory and using pinned memory



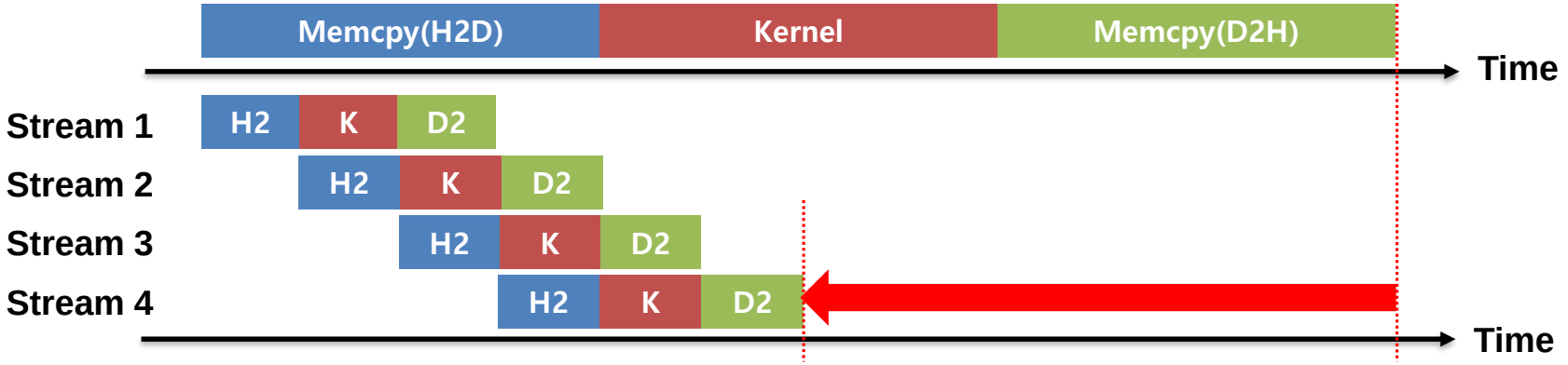
# CUDA Stream in a Device

- *Stream* is a queue of CUDA operations which are issued in order


- Multiple streams issue operations independently, but multiple (H2D copies / Kernels / D2H copies) cannot be executed simultaneously within a device




- We can hide most memory copy overhead (PCIe traffic) via overlapping many streams



# Asynchronous Memory Copy

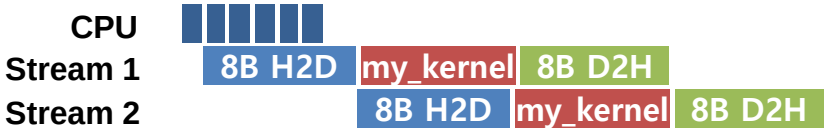
- Asynchronous memory copy is necessary to use streams
  - Asynchronous: enqueue the job and control returns to CPU immediately
  - c.f. Synchronous: enqueue the job and wait until it finishes, then control returns to CPU
- Examples: copying 16 bytes using synchronous or asynchronous copy

```
cudaMemcpy(device, host, 16, cudaMemcpyHostToDevice);
my_kernel<<<blocks, threads, 0>>>(device, 16);
cudaMemcpy(host, device, 16, cudaMemcpyDeviceToHost);
```

※ kernel launches are always asynchronous


```
cudaMemcpyAsync(device, host, 16, cudaMemcpyHostToDevice, stream1);
my_kernel<<<blocks, threads, 0, stream1>>>(device, 16);
cudaMemcpyAsync(host, device, 16, cudaMemcpyDeviceToHost, stream1);
```


```
cudaMemcpyAsync(device, host, 8, cudaMemcpyHostToDevice, stream1);
cudaMemcpyAsync(device+8, host+8, 8, cudaMemcpyHostToDevice, stream2);
my_kernel<<<blocks, threads, 0, stream1>>>(device, 8);
my_kernel<<<blocks, threads, 0, stream2>>>(device+8, 8);
cudaMemcpyAsync(host, device, 8, cudaMemcpyDeviceToHost, stream1);
cudaMemcpyAsync(host+8, device+8, 8, cudaMemcpyDeviceToHost, stream2);
```



# Synchronization – Using Default Stream

- If the stream is not specified, jobs are enqueued in the *default stream* (stream 0)
- Default stream is not overlapped with other streams
- We can use this to operate synchronization throughout all streams
  - Example: running the last synchronizing kernel after all previous asynchronous jobs end

```
cudaMemcpyAsync(device, host, 8, cudaMemcpyHostToDevice, stream1);
cudaMemcpyAsync(device+8, host+8, 8, cudaMemcpyHostToDevice, stream2);
my_kernel<<<blocks, threads, 0, stream1>>>(device, 8);
my_kernel<<<blocks, threads, 0, stream2>>>(device+8, 8);
cudaMemcpyAsync(host, device, 8, cudaMemcpyDeviceToHost, stream1);
cudaMemcpyAsync(host+8, device+8, 8, cudaMemcpyDeviceToHost, stream2);
last_kernel<<<blocks, threads, 0>>>(device, 16);
cudaMemcpy(host, device, 16, cudaMemcpyDeviceToHost);
```

# Synchronization – Using CUDA APIs

- Some APIs are provided only for synchronization
  - Use `cudaStreamSynchronize()` to synchronize jobs in a stream
  - Use `cudaDeviceSynchronize()` to synchronize every previous jobs in a device
  - Use CUDA events (out of this presentation's scope)

```
1 cudaMalloc(…);
2 cudaMemcpyAsync(…H2D…);
3 my_kernel<<<…>>>(…);
4 cudaMemcpyAsync(…D2H…);
5 cudaDeviceSynchronize();
```

Line 1 finished

Line 2 may not have finished

Line 2, 3 may not have finished

Line 2, 3, 4 may not have finished

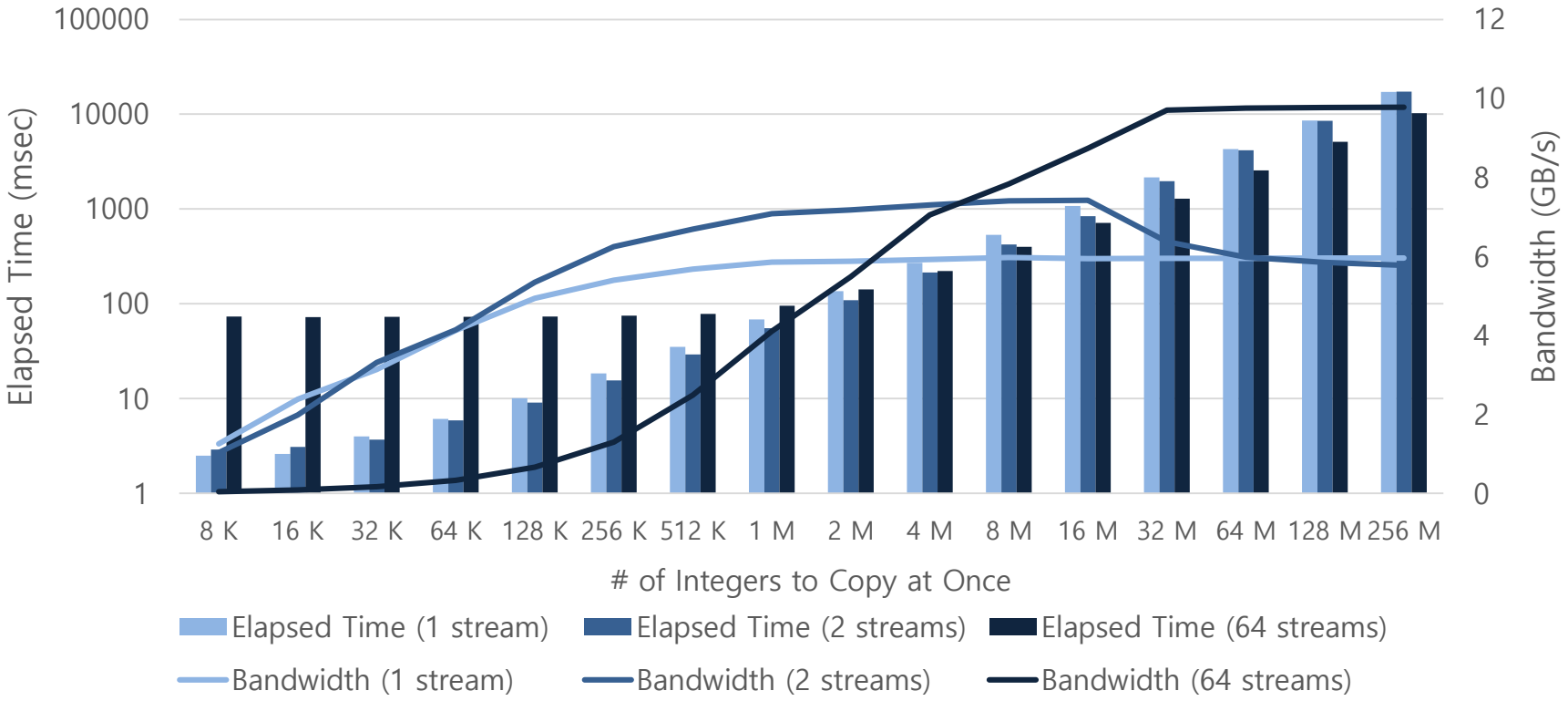
Line 2, 3, 4 finished

- Synchronization degrades performance – use it only when it is necessary

- Be careful not to be unaware of using synchronous APIs
  - e.g. `cudaMalloc()` or `cudaFree()` synchronizes the device
  - Check the CUDA API document to be sure whether an API has synchronous properties

# Example: Memory Copy with Multiple Streams

- Run `make busy_copy` to compile `src/busy_copy/main.cu`
- Similar with `simple_copy` but uses pinned memory only and uses multiple streams
- Run `./busy_copy 1048576 2` to copy 1M integers using 2 streams
- Check the elapsed time and bandwidth while increasing the number of streams
  - The number of streams should be power of 2 for exact comparisons



# CUDA Kernel

- Implementing an optimized CUDA kernel requires huge effort
- We can use provided libraries instead to reduce time
  - e.g. NVIDIA Deep Learning SDK (visit https://developer.nvidia.com/deep-learning-software)

- Though we use provided libraries, we need to understand GPU and CUDA to use them properly

- Sometimes we also need to implement a new kernel for untypical operations

# CUDA Kernel Programming Architecture

- GPU computation cores are divided in several *streaming multiprocessors* (*SM*s or *MP*s)
  - # of SMs depends on devices
- *Warp*: a set of 32 threads
  - The scheduling unit of a SM → threads in a warp are always synchronized with each other!
  - Supports *shuffle instructions* between threads in a warp, such as `__shfl_up()`, `__shfl_xor()`, etc.
  - # of warps per SM depends on *CUDA compute capability*
  - Maximum # of resident threads = (# of SMs) * (# of warps per SM) * (32 threads per warp)
    - e.g. GTX 1080: (20 SMs) * (4 warps per SM) * (32 threads per warp) = 2560 resident threads
- *Block*: a set of one or more threads
  - Maximum # of threads per block depends on devices
    - e.g. GTX 1080: 1024 threads per block
  - Threads in a block shares a specified amount of *shared memory* (faster access than global memory)
  - Threads in a block can be synchronized via `__syncthreads()`
- *Grid*: a set of one or more blocks
  - All blocks are basically independent, no API for synchronization
  - We can use some signaling APIs between blocks instead, such as memory fence or atomic operations

# Kernel Implementation Tips – 1

- Don’t branch the context of the kernel
  - Use if-else as less as possible
  - Make the condition constant during the runtime
    - Comparison between constants are calculated during compilation
    - Use C++ template to make some user-decided variables constant
  - Branching inside a warp makes the performance terrible
- Memory access optimization
  - Sequential access is much faster than random access
  - Remember that memory access is much slower than calculations
  - Read data as much as possible at once
  - Let frequently accessed data be in shared memory or local memory
- Warp optimization
  - Make the best use of shuffle instructions
  - Never branch in a warp
  - Always let threads in a warp be in the same block
- Synchronization
  - Overhead Comparison: Device Sync > Stream Sync >> Using Event > Block Sync
  - Utilize features of warps or shared memory to reduce synchronization

# Kernel Implementation Tips – 2

- Deciding GPU resource usage
  - Always compute the maximum # of resident threads in the code and store it as a constant
  - Decide the # of threads per block according to your usage plan of shared memory
    - Usually 256, 512, or 1024 is used
  - Always let the # of threads per block power of 2 and larger than or equal to 32
    - 32, 64, 128, 256, 512, or 1024
  - Don't let the # of threads in a grid exceed the maximum # of resident threads
  - If there are many kinds of kernels to be executed in parallel, hand out resident threads according to workload amount
  - If kernels to be executed are serial, provide the whole resident threads to every kernel executions

- Profiling
  - Find out which kernels are slow via measuring pure kernel latency without memory copy
  - Measure with different size of workload to know in which state the kernel performs best
  - Profiling tools like `nvprof` and `nvvp` may reduce profiling effort

# Example: Reduction

- Run `make reduction` to compile `src/reduction/main.cu` and `reduction.cuh`
- Run `./reduction 1024` to test adding 1024 integers
- Reading and understanding `reduction.cuh` may be very helpful to understand basic kernel programming

# Useful References

- CUDA streams: best practices and common pitfalls
  http://on-demand.gputechconf.com/gtc/2014/presentations/S4158-cuda-streams-best-practices-common-pitfalls.pdf
- CUDA C/C++ Streams and Concurrency
  http://on-demand.gputechconf.com/gtc-express/2011/presentations/StreamsAndConcurrencyWebinar.pdf
- Optimizing Parallel Reduction in CUDA
  http://developer.download.nvidia.com/compute/cuda/1.1-Beta/x86_website/projects/reduction/doc/reduction.pdf
- Parallel Prefix Sum (Scan) with CUDA
  http://http.developer.nvidia.com/GPUGems3/gpugems3_ch39.html

**Thank You.**