NYU
New York University

CSCI-UA.0480-003

Parallel Computing

Lecture 22: CUDA – Last Touch

Mohamed Zahran (aka Z)
mzahran@cs.nyu.edu
http://www.mzahran.com

Some Advanced Topics

- Overlapping computation and data transfer
- Asynchronous execution
- Multi-GPU systems

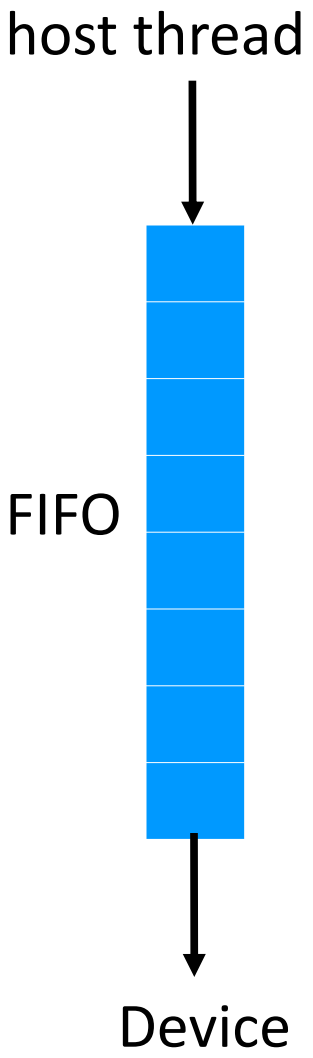
Streams

Overlapping Computation and Data-transfer: Streams

- A sequence of operations that execute on the device in the order in which they are issued by the host code
- Operations in different streams can be interleaved and, when possible, they can even run concurrently.
- A stream can be sequence of kernel launches and host-device memory copies
- Can have several open streams to the same device at once
- Need GPUs with concurrent transfer/execution capability
- Potential performance improvement: can overlap transfer and computation

Streams

- By default all transfers and kernel launches are assigned to stream 0
  - This means they are executed in order



Example: Default Stream

```
cudaMemcpy(d_a, a, numBytes, cudaMemcpyHostToDevice);
    increment<<<1,N>>>(d_a) ;
cudaMemcpy(a, d_a, numBytes, cudaMemcpyDeviceToHost);
```

- In the code above, from the perspective of the device, all three operations are issued to the same (default) stream and will execute in the order that they were issued.
- From the perspective of the host:
  - data transfers are blocking or synchronous transfers
  - kernel launch is asynchronous.

Isn't this more efficient?

```
cudaMemcpy(d_a, a, numBytes, cudaMemcpyHostToDevice);
increment<<<1,N>>>(d_a) ;
anyCPUfunction();
cudaMemcpy(a, d_a, numBytes, cudaMemcpyDeviceToHost);
```

Example: Non-Default Stream

Non-default streams in CUDA C/C++ are declared, created, and destroyed in host code as follows:

```
cudaStream_t stream1;
cudaError_t result;
result = cudaStreamCreate(&stream1);
result = cudaStreamDestroy(stream1);
```

To issue data transfer to non-default stream (non-blocking):

```
result = cudaMemcpyAsync(d_a, a, N, cudaMemcpyHostToDevice, stream1);
```

To launch a kernel to non-default stream:

```
increment<<<1,N,0,stream1>>>(d_a);
```

Important

- All operations in non-default streams are non-blocking with respect to the host code.
- Sometimes you need to synchronize the host code with operations in a stream.
- You have several options:
  - cudaDeviceSynchronize() → blocks host
    - Blocks until the device has completed all preceding requested tasks.
  - cudaStreamSynchronize(stream) → blocks host
    - Blocks until stream has completed all operations.
  - cudaStreamQuery(stream) → does not block host
    - Returns cudaSuccess if all operations in stream have completed, or cudaErrorNotReady if not (both of type cudaError_t)

Streams

- The amount of overlap execution between two streams depends on:
  - Device supports overlap transfer and kernel execution
  - Devices supports concurrent kernel execution
  - Device supports concurrent data transfer
  - The order on which commands are issued to each stream

Using streams to overlap device execution with data transfer

- Conditions to be satisfied first:
  - The device must be capable of *concurrent transfer and execution*.
  - The kernel execution and the data transfer to be overlapped must both occur in *different, non-default* streams.
  - The host memory involved in the data transfer must be *pinned* memory.

Pinned Pages

- Allocate page(s) from system RAM (cudaMallocHost())
  - Cannot be paged out
  - Enables highest memory copy performance (cudaMemcpyAsyc())
- If too much pinned pages, overall system performance may greatly suffer.

Using streams to overlap device execution with data transfer

```
for (int i = 0; i < nStreams; ++i) {

    int offset = i * streamSize;

    cudaMemcpyAsync(&d_a[offset], &a[offset],
    streamBytes, cudaMemcpyHostToDevice, stream[i]);

    kernel<<<Nblks, Nthreds, stream[i]>>>(d_a, offset);

    cudaMemcpyAsync(&a[offset], &d_a[offset],
    streamBytes, cudaMemcpyDeviceToHost, stream[i]);
}
```

So..

- Streams are a good way to overlap execution and transfer, hardware permits.
- Don't confuse kernels, threads, and streams.

Asynchronous Execution

Asynchronous Execution

- Asynchronous = returns to host right-away and does not wait for device
- This includes:
  - Kernel launches;
  - Memory copies between two addresses to the same device memory;
  - Memory copies from host to device of a memory block of 64 KB or less;
  - Memory copies performed by functions that are suffixed with Async;

Asynchronous Execution

- Some CUDA API calls and all kernel launches are asynchronous with respect to the host code.
- This means error-reporting is also asynchronous.
- Asynchronous transfer (cudaMemcpyAsync()) version *requires pinned host memory*
- On all CUDA-enabled devices, it is possible to overlap host computation with asynchronous data transfers and with device computations.

Asynchronous Execution

```
cudaMemcpyAsync(a_d, a_h, size, cudaMemcpyHostToDevice, 0);
kernel<<<grid, block>>>(a_d);
cpuFunction();
```

Other Sources of Concurrency

- Some devices of compute capability 2.x and higher can execute multiple kernels concurrently.
- The maximum number of kernel launches that a device can execute concurrently is 32 on devices of compute capability 3.5 and 16 on devices of lower compute capability.
- A kernel from one CUDA context cannot execute concurrently with a kernel from another CUDA context. A CUDA context is the application.
  - However, check Multi-Process Service (MPS)

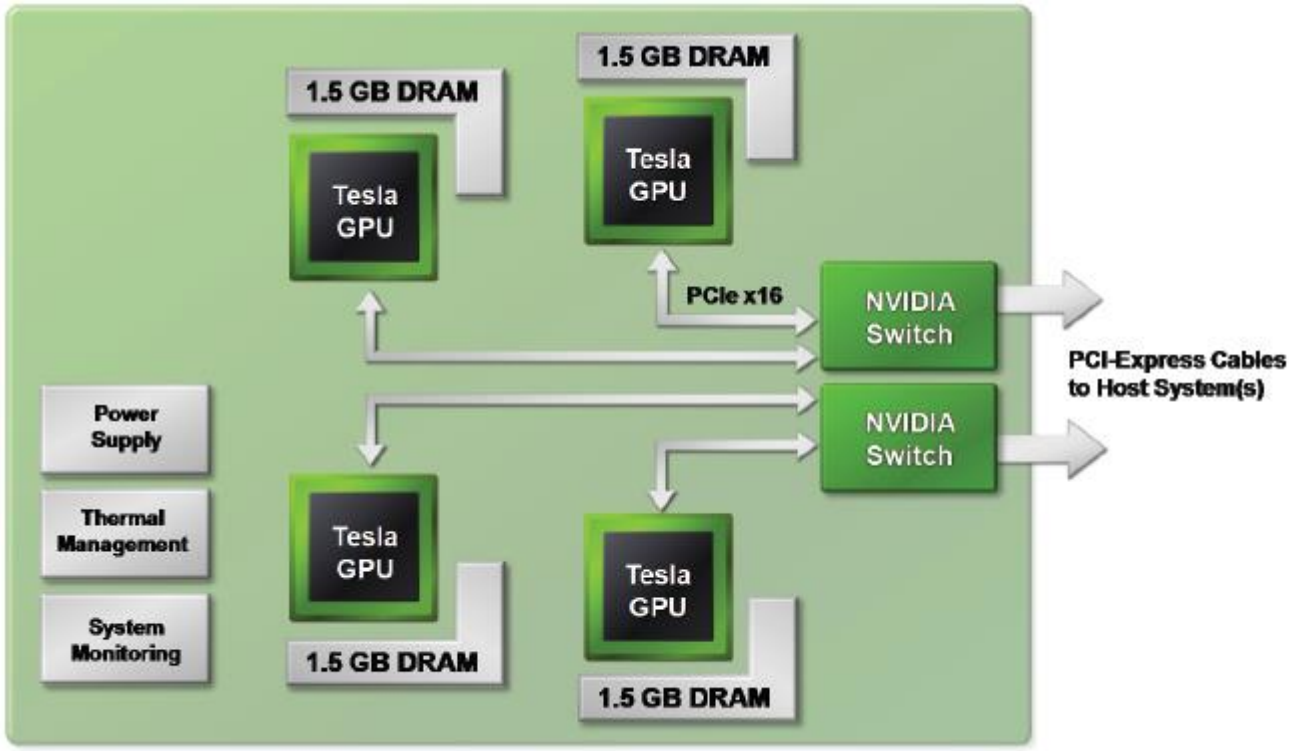
Multi-GPU Systems

Multi-GPU systems: Flavors

- Multiple GPUs in the same node (e.g. PC)
- Multi-node system (e.g. MPI).

Multi-GPU configuration is here to stay!

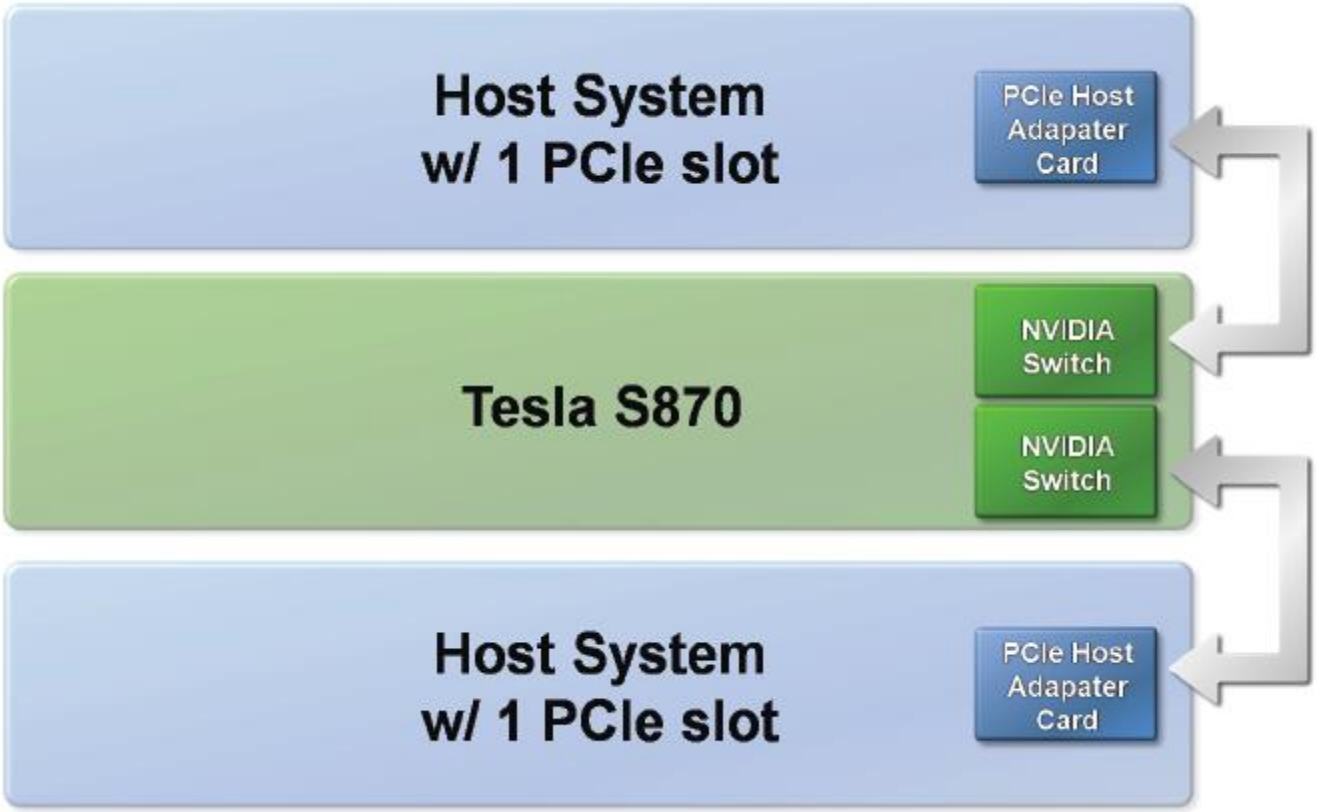
Hardware Example: Tesla S870 Server



Hardware Example: Tesla S870 Server

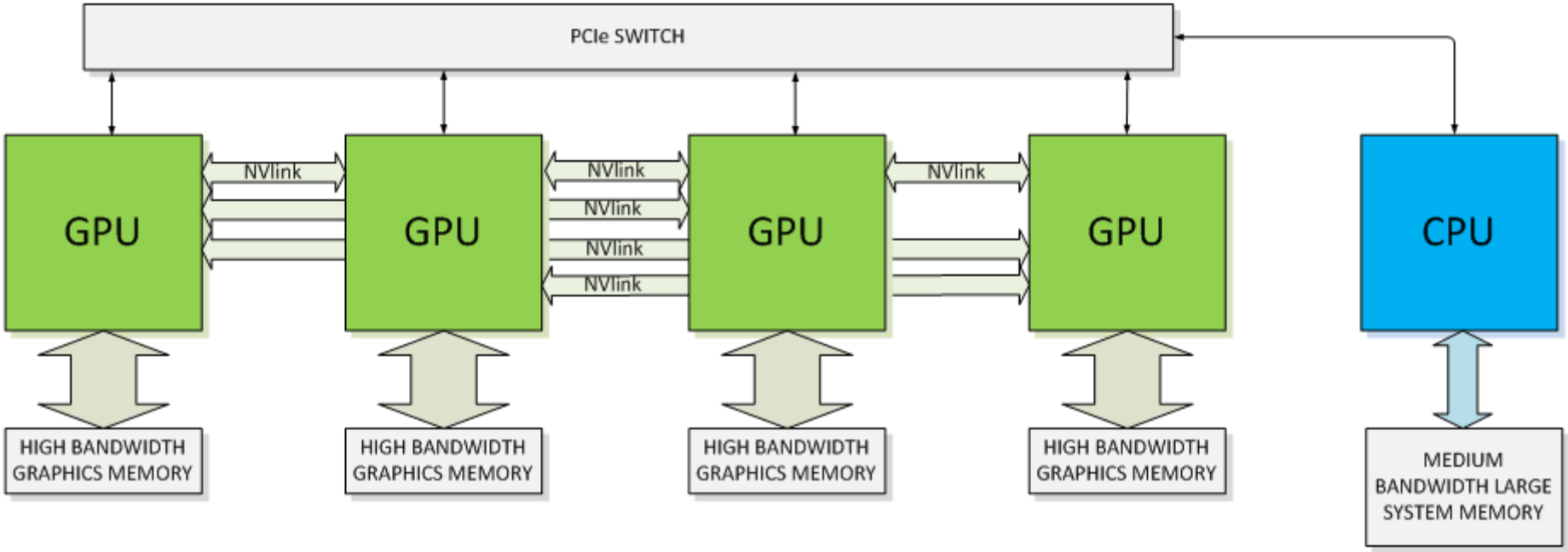
Connected to a single-host

Hardware Example: Tesla S870 Server



Connected to a two host systems

NVLINK
(PASCAL Architecture … Circa 2016)



Why Multi-GPU Solutions

- Scaling-up performance
- Another level of parallelism
- Power
- Reliability

```
// Run independent kernel on each CUDA device
int numDevs= 0;
cudaGetDeviceCount(&numDevs);
…
for (int d = 0; d < numDevs; d++) {
        cudaSetDevice(d);
        kernel<<<blocks, threads>>>(args);
}
```

CUDA Support

- cudaGetDeviceCount(int * count)
  - Returns in *count the number of devices
- cudaGetDevice (int * *device*)
  - Returns in *device the device on which the active host thread executes the device code.

CUDA Support

- cudaSetDevice(devID)
  - Device selection within the code by specifying the identifier and making CUDA kernels run on the selected GPU.

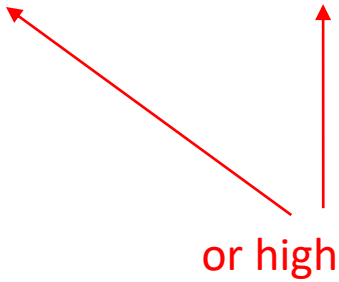
```
size_t size = 1024 * sizeof(float);
cudaSetDevice(0);              // Set device 0 as current
float* p0;
cudaMalloc(&p0, size);         // Allocate memory on device 0
MyKernel<<<1000, 128>>>(p0); // Launch kernel on device 0
cudaSetDevice(1);              // Set device 1 as current
float* p1;
cudaMalloc(&p1, size);         // Allocate memory on device 1
MyKernel<<<1000, 128>>>(p1); // Launch kernel on device 1
```

Last Note About Compilation

OpenMP and CUDA

- File *.cu
- include both cuda.h and omp.h

```
nvcc -arch=compute_30 -code=sm_30 -Xcompiler -fopenmp prog.cu
```



MPI and CUDA

- With Kepler class and later GPUs & Hyper-Q, multiple MPI processes can share the GPU
- You execute with mpirun or mpiexec
- Implementations of CUDA-aware MPI are available from several sources:
  - **MVAPICH2**
  - **IBM™ Spectrum MPI.**
  - **The Open MPI Project**

Conclusions

- There are many performance enhancement techniques in our arsenal:
  - Streams
  - Texture memory
  - Asynchronous execution
  - …
- Multi-GPU system:
  - is an efficient way to reach higher performance
  - Performance gain is application-dependent and programmer-dependent!