EN 600.320/420 Parallel Programming

CUDA C Programming



What Is CUDA?

- CUDA: Compute Unified Device Architecture
 Created by NVIDIA
- A way to perform computation on the GPU
- Specification for:
 - A computer architecture
 - A language
 - An application interface (API)

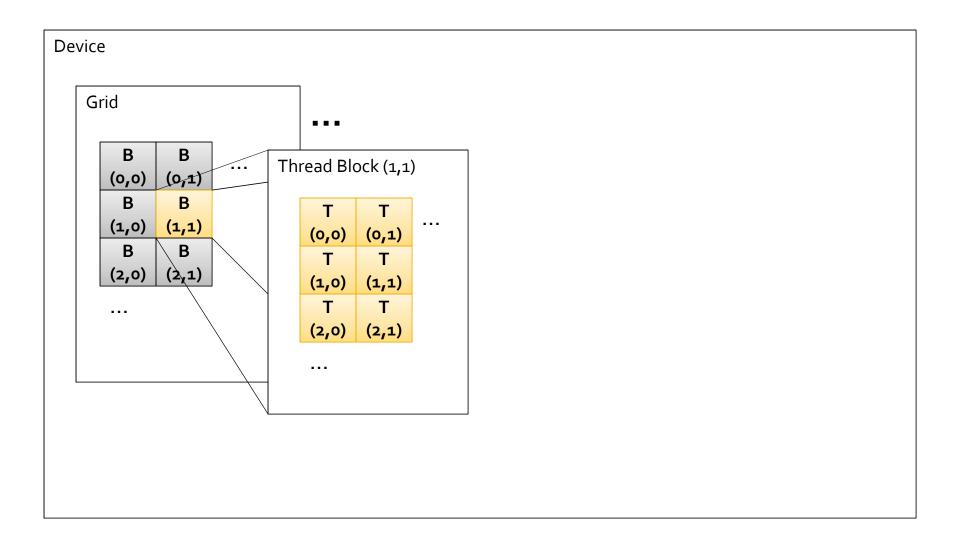
CUDA Execution Model

- A CUDA device is a highly parallel processor
- We assume it can execute many hundreds of threads in parallel
- Threads to Stream Processors ratio > 1
- When writing CUDA software, think in terms of threads, not processors
- Startup and Context Switching costs per thread are very low!!

CUDA Execution Model

- The CUDA programming model imposes a data decomposition approach
- The grid is the data domain (1D, 2D or 3D)
- The grid is decomposed into thread blocks
- A thread block is decomposed into threads

CUDA Data Decomposition



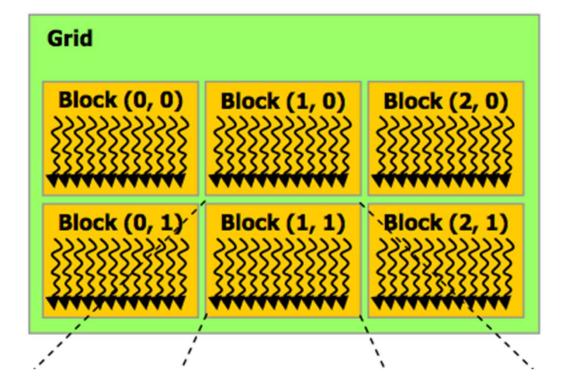
CUDA Execution Model

- Thread blocks and threads are given unique identifiers
- Identifiers can be 1D, 2D or 3D
- Used by the kernel to identify which part of a problem to work on
 - E.g. which data from memory to read, etc.

CUDA Kernel

- A kernel is a program that processes a single data element
- A thread runs the kernel on a data element

Grid->Blocks->Threads

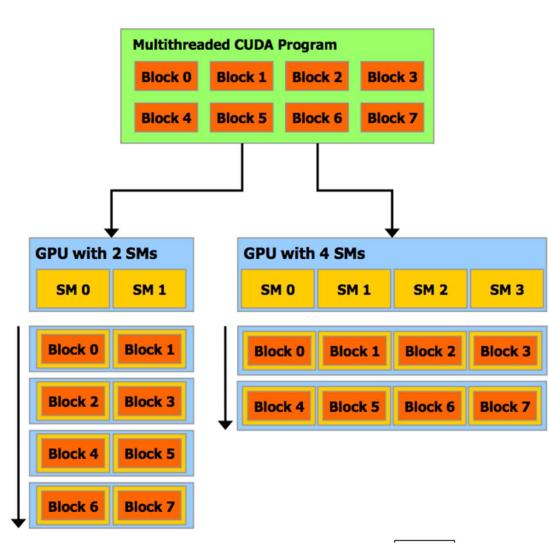


CUDA Execution Model

Thread Blocks

- A thread block may have up to 512 threads
- All threads in a thread block are run on the same multi-processor
 - Thus can communicate via shared memory
 - And synchronize
- Threads of a block are multiplexed onto a multi-processor as *warps*

Thread Block Scheduling



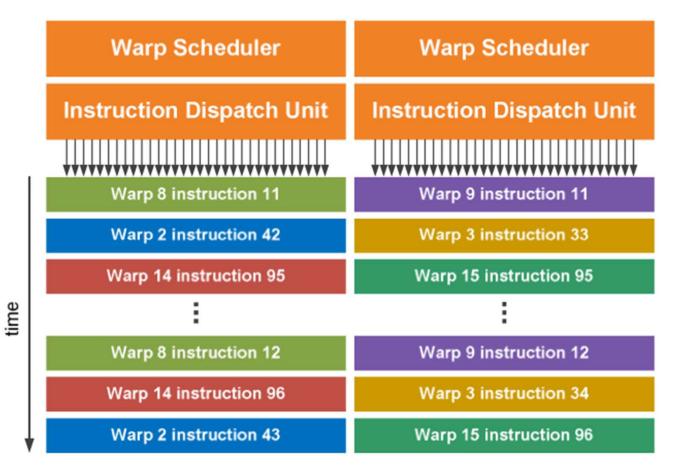
Warps

- Warps are groups of 32 threads
- Warps are the fundamental scheduling unit of the processor
 - Dispatched two at a time to 16 processors each (on Fermi)
- Each warp forms a SIMD group
 - Thread blocks are not SIMD, Warps are!

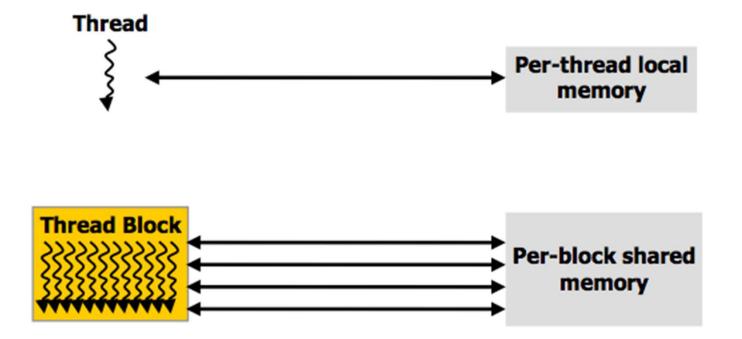
Warp Scheduling

Dual issue instructions

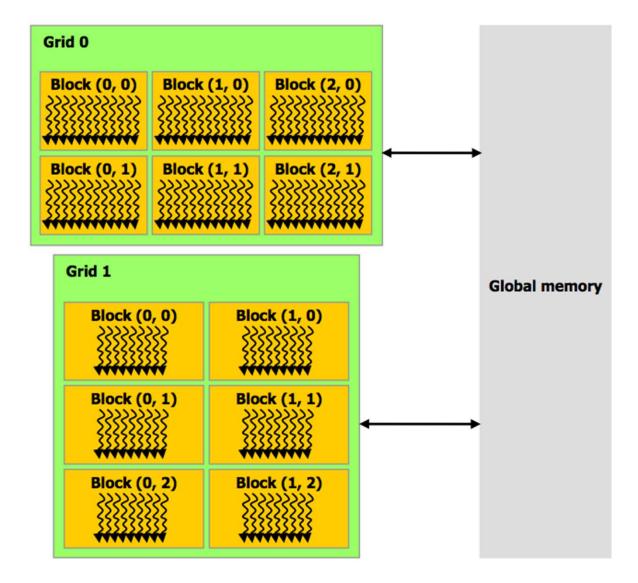
- 32 threads
- 16 cores
- 2 units/SM



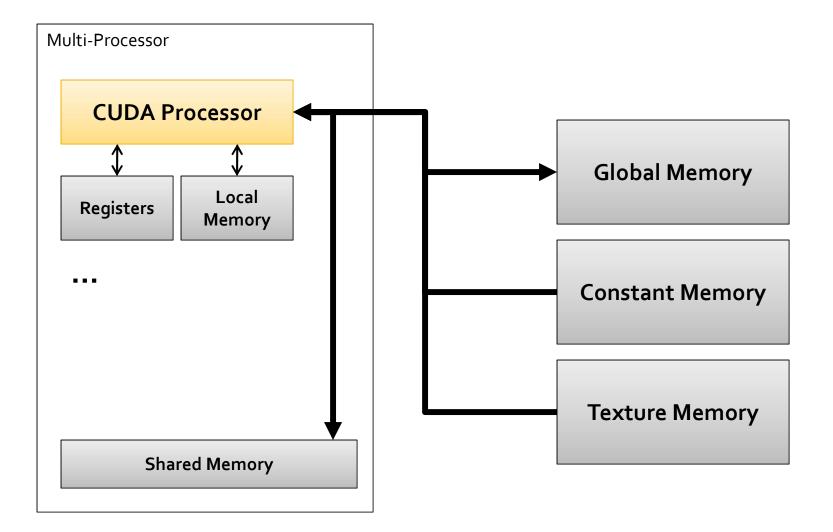
Memory Addressibility



Memory Addressibility



CUDA Memory Hierarchy



CUDA Memory Hierarchy

CUDA Processors have access to:

Memory Type	Access	Sharing
Registers	Read/Write	Private
Local Memory	Read/Write	Private
Shared Memory	Read/Write	Multi-Processor
Global Memory	Read/Write	Device
Constant Memory	Read	Device
Texture Memory	Read	Device

CUDA Memory Model

Registers

- Large number of registers per stream processor (1024)
- Zero-clock cycle access
- Store either 64 bit integer or 64 bit float

CUDA Memory Model

Shared Memory

- A block of memory that is shared by all stream processors in a multi-processor
 - 48 or 16K per SM in Fermi
- 16KB per block, stored in 16x1KB banks
- Very fast to access (i.e. as fast as registers!) without bank conflicts

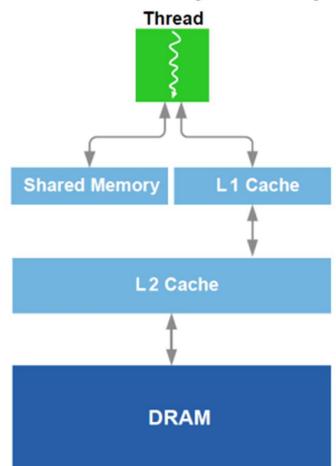
CUDA Memory Model

Global Memory

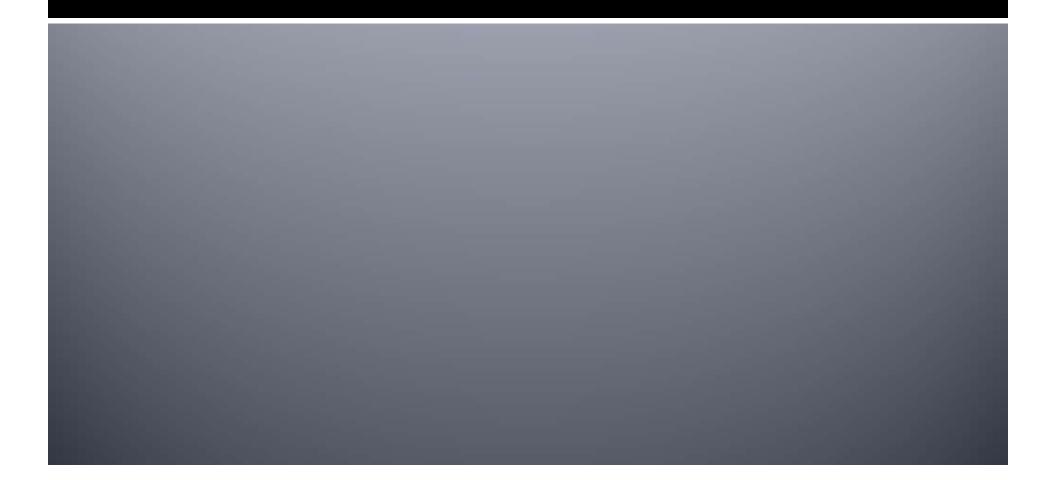
- The large block of memory shared by all multi-processors on the compute device
- Size depends on device 256MB to 24GB (Tesla K80 is 2x 12GB)
- High bandwidth (K8o is 48o GB/s)
- Slow to access several hundred clock cycle latency.

Fermi Memory Model

Fermi Memory Hierarchy



First CUDA Program



CUDA Program

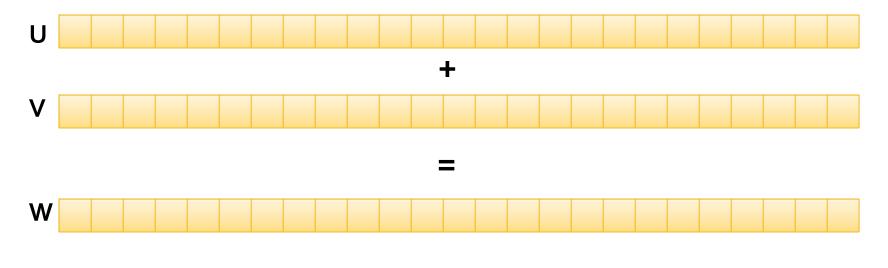
 We will create a simple CUDA program to add two vectors

•
$$U = \{U_0, U_1, \dots, U_n\}$$

• $V = \{V_0, V_1, \dots, V_n\}$

• W = U + V = {
$$U_0 + V_0, U_1 + V_1, \dots U_n + V_n$$
}

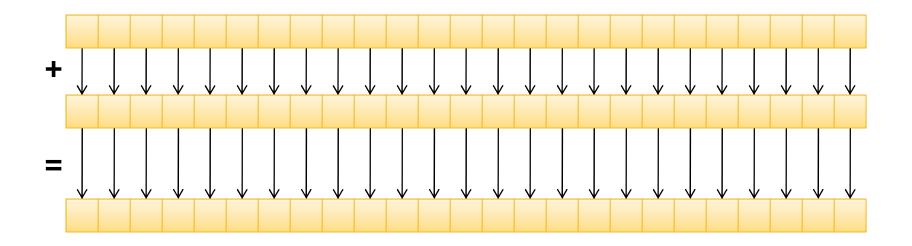
Vector-Vector Addition



 $W = U + V \quad W_i = U_i + V_i$

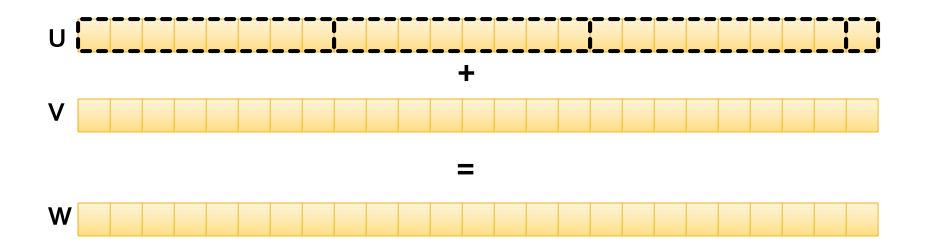
Easy to parallelize: Each element is independent!

Threads

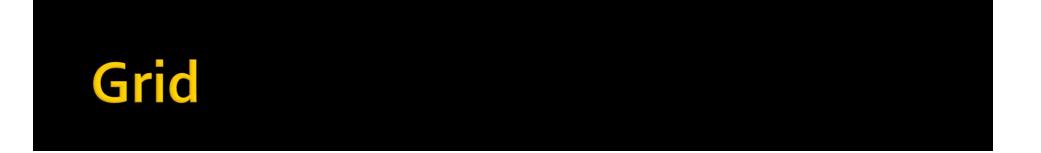


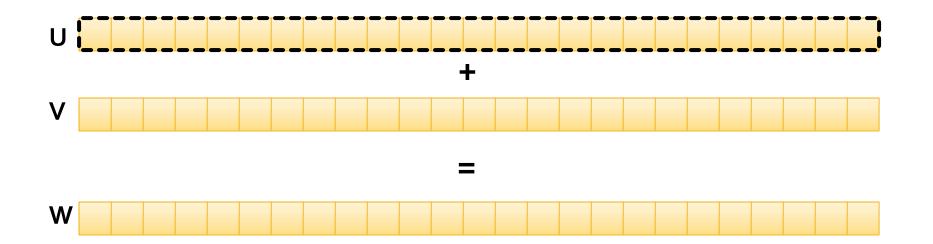
Threads: Each element is computed by a separate thread

Thread Blocks



- Blocks: Group sets of adjacent elements into blocks
 - To conform with device parameters





• Grid: The entire vector

Device Code

 Our program will be a single source file, with two parts:

Device Code

 A kernel to perform the addition of two elements

Kernel Function

```
__global__ void VectorAdditionKernel(
    const float* pVectorA,
    const float* pVectorB,
    float* pVectorC)
{
    unsigned int i = blockIdx.x * blockDim.x + threadIdx.x;
    pVectorC[i] = pVectorA[i] + pVectorB[i];
}
```

CUDA Language

- CUDA defines a language that is similar to C/C++
- CUDA source code contains a mix of *host* and *device* code and data

CUDA Language

- CUDA defines a language that is similar to C/C++
- Important Differences:
 - Runtime Library
 - Functions
 - Classes, Structs, Unions

CUDA Runtime Library

- Code that runs on the device can't use normal
 C/C++ Runtime Library functions
- No printf, fread, malloc, etc
- Most math functions have device equivalent

CUDA Runtime Functions

- There are a number of device specific functions/intrinsics available:
 - syncThreads
 - mul24
 - atomicAdd, atomicCAS, atomicMin, ...

Functions

- On a CUDA device, there is no stack
- By default, all function calls are inlined
- All local variables, function arguments are stored in registers
- NO function recursion
- No function pointers

CUDA Language

- CUDA defines a language that is similar to C/C++
- Syntactic extensions:
 - Declaration Qualifiers
 - Built-in Variables
 - Built-in Types
 - Execution Configuration

Declspec's

- Declspec = declaration specifier / declaration qualifier
- A modifier applied to declarations of:
 - Variables
 - Functions
- Examples: const, extern, static

CUDA Function Declspec's

- CUDA uses the following declapecs for functions:
- __device__
- host____
- __global___



- Declares that a function is compiled to, and executes on the device
- Callable only from another function on the device



- Declares that a function is compiled to and executes on the host
- Callable only from the host
- Functions without any CUDA declapec are host by default



- Declares that a function is compiled to and executes on the device
- Callable from the host
- Used as the entry point from host to device

Kernel Function

```
__global__ void VectorAdditionKernel(
    const float* pVectorA,
    const float* pVectorB,
    float* pVectorC)
{
    unsigned int i = blockIdx.x * blockDim.x + threadIdx.x;
    pVectorC[i] = pVectorA[i] + pVectorB[i];
}
```

Vector Types

- Can construct a vector type with special function: make_{typename}(v₀, v₁, ...)
- Can access elements of a vector type with ".x", ".y", ".z", ".w": vecvar.x
- dim3 is a special vector type for grids, same as uint3

Built-in Variables

- CUDA provides four global, built-in variables
 threadIdx, blockIdx, blockDim, gridDim
- Typed as a 'dim3' or 'uint3'
- Accessible only from device code
- Cannot take address
- Cannot assign value

Host Code

 Our program will be a single source file, with two parts:

Host Code

- Allocate GPU memory for vector
- Copy vector from host to device memory
- Launch kernel
- Copy vector from device to host memory

Kernel Function

```
__global__ void VectorAdditionKernel(
    const float* pVectorA,
    const float* pVectorB,
    float* pVectorC)
{
    unsigned int i = blockIdx.x * blockDim.x + threadIdx.x;
    pVectorC[i] = pVectorA[i] + pVectorB[i];
}
```

Host Code – Copy Data To GPU

```
float* pDeviceVectorA = 0;
float* pDeviceVectorB = 0;
float* pDeviceVectorC = 0;
```

. . .

```
cudaMalloc((void**)&pDeviceVectorA, VectorSize);
cudaMalloc((void**)&pDeviceVectorB, VectorSize);
cudaMalloc((void**)&pDeviceVectorC, VectorSize);
```

```
cudaMemcpy(pDeviceVectorA, pHostVectorA,
    VectorSize, cudaMemcpyHostToDevice);
cudaMemcpy(pDeviceVectorB, pHostVectorB,
    VectorSize, cudaMemcpyHostToDevice);
```

Allocating Memory

- There is no malloc or free function that can be called from device code
 → How can we allocate memory?
- From the host with cudaMalloc()
 - And copy data in from host to initialize

Host Code

```
bool VectorAddition(
    unsigned N,
    const float* pHostVectorA,
    const float* pHostVectorB,
    float* pHostVectorC)
{
    const unsigned BLOCKSIZE = 512;
    unsigned ThreadCount = N;
    unsigned BlockCount = N / BLOCKSIZE;
    unsigned VectorSize = ThreadCount * sizeof(float);
    ...
```

Host Code – Execute Kernel

. . .

VectorAdditionKernel<<<BlockCount,BLOCKSIZE>>>(
 pDeviceVectorA,
 pDeviceVectorB,
 pDeviceVectorC);

 CUDA provides syntactic sugar to launch the execution of kernels

Func<<<GridDim, BlockDim>>>(Arguments, ...)

Func<<<GridDim, BlockDim>>>(Arguments, ...)

Func is a __global___ function

Func<<<GridDim, BlockDim>>>(Arguments, ...)

 GridDim is a 'dim3' typed expression giving the size of the grid (i.e. problem domain)

Func<<<GridDim, BlockDim>>>(Arguments, ...)

 BlockDim is a 'dim3' typed expression giving the size of a thread block

Func<<<GridDim, BlockDim>>>(Arguments, ...)

 The compiler turns this type of statement into a block of code that configures, and launches the kernel

Host Code – Read result from GPU

. . .

CUDA Variable Declspec's

- CUDA uses the following declaration qualifiers for variables:
- __device__
- __shared___
- __constant_
- Only apply to global variables



- Declares that a global variable is stored on the device
- The data resides in global memory
- Has lifetime of the entire application
- Accessible to all GPU threads
- Accessible to the CPU via API



- Declares that a global variable is stored on the device
- The data resides in shared memory
- Has lifetime of the thread block
- Accessible to all threads, one copy per thread block



- If not declared as volatile, reads from different threads are not visible unless a synchronization barrier used
- Not accessible from CPU

constant

- Declares that a global variable is stored on the device
- The data resides in constant memory
- Has lifetime of entire application
- Accessible to all GPU threads (read only)
- Accessible to CPU via API (read-write)

Vector Size

What if the vector size is not an integral number of blocks?

• Option 1:

Perform bounds checking in kernel

Option 2:

Pad out the vector to correct length

Maximum Vector Size

- Grid is 1-dimensional
- Maximum of 512 threads in a block
- Maximum of 65536 blocks in a 1D grid
 Maximum vector size is 65536 times 512
- How do we operate on a vector larger than 16M elements?

Maximum Vector Size

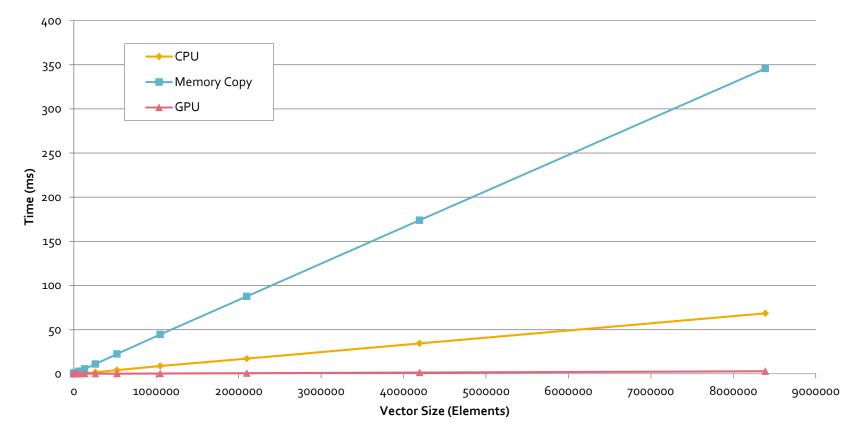
- How do we operate on a vector larger than 16M elements?
- Option 1:
 - Use a 2-D indexing scheme
- Option 2:
 - Compute with several grids

Performance

- The GPU is faster than the CPU
- But, computing on the GPU involves overhead:
 - → Must get data to/from the GPU
- Where is the "break-even" point?

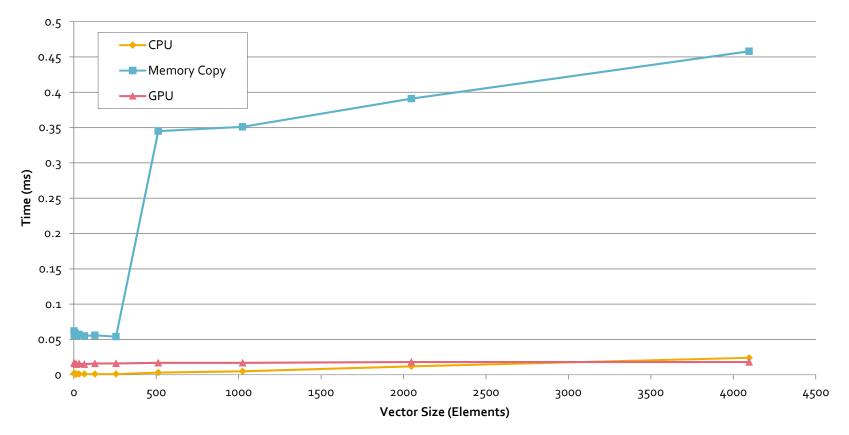
Vector Addition Performance

CUDA Vector-Vector Addition Performance



Vector Addition Performance

CUDA Vector-Vector Addition Performance



Performance Conclusion

- Matrix addition is not a good CUDA program
 - Why? In terms of Roofline? Not enough operational intensity
- Never overcome the data transfer
 - Not enough computation
 - Better on the CPU