

Parallel Programming

CUDA Programming Model

Overview

- CUDA programming model
 - Host code and device code (kernel)
 - CUDA Threads: Grids, Blocks
 - CUDA memory allocation and copy
 - Kernel programs and their invocation
- Simple CUDA program examples

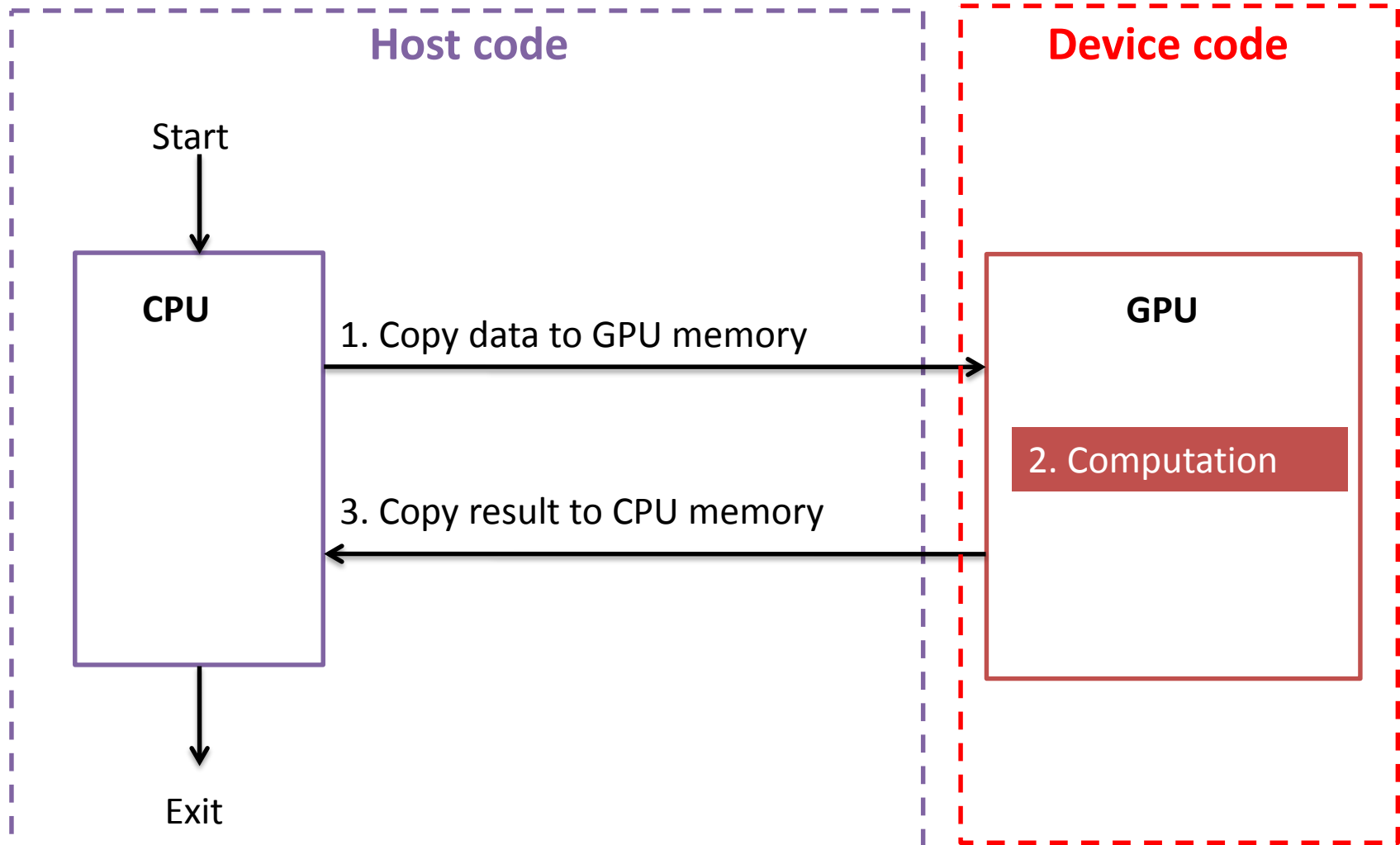
CUDA: Compute Unified Device Architecture

- A parallel computing architecture developed by NVIDIA.
 - Hardware: NVIDIA GPUs, from embedded devices, graphics cards for laptops and desktops, to dedicated server products for computation.
 - Software
 - Tool kit, device drivers, and programming SDK.
 - Support C, Fortran, Matlab, and other languages.
- We teach CUDA C programming in this course

Host and Device Code

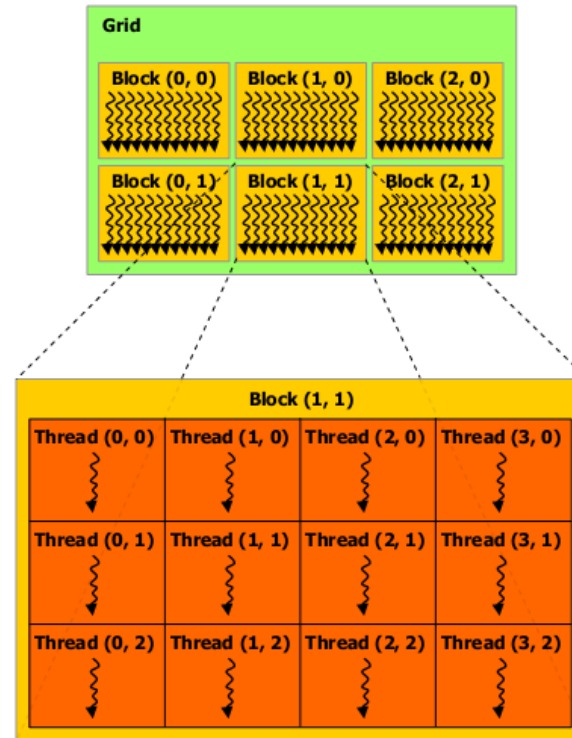
- A CUDA program consists of two parts: *host* and *device* (or *kernel*) code.
- Host code: executed on the CPU
 - Memory copy between the GPU and the CPU
 - Computation on the CPU and call GPU kernel
- Device code: executed on the GPU
 - GPU-based computation
- A CUDA program always starts from the host code, and then invokes the GPU kernels.

Processing Flow of a CUDA Program



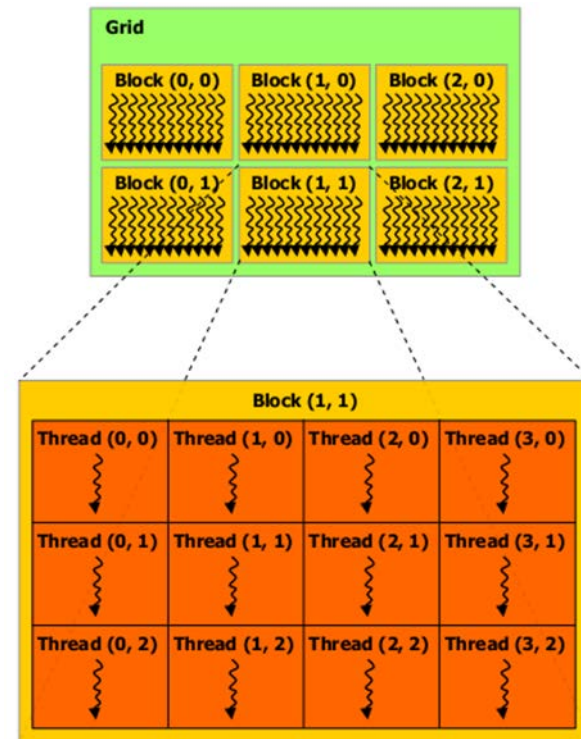
Threads in a CUDA Kernel

- Each kernel corresponds to a **grid** of threads.
- Each grid consists of multiple thread **blocks**.
- Each thread block contains multiple **threads**.



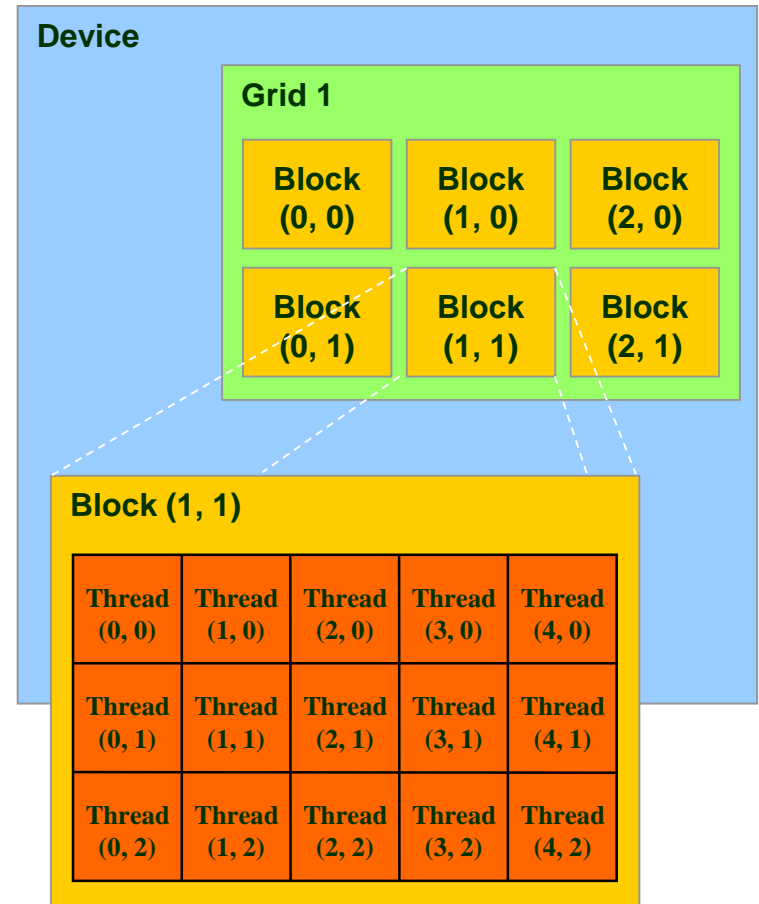
Grid and Block Dimensions

- A grid can be one-dimension or two-dimension in number of **blocks**. (gridDim.z unused)
 - gridDim.x, gridDim.y
- A thread block can be one-dimension, two-dimension, or three-dimension in number of **threads**.
 - blockDim.x, blockDim.y, blockDim.z.
- Any unspecified dimension is set to size 1.



Block and Thread IDs

- Threads and blocks have built-in IDs
 - Block ID: 1D or 2D (z dimension is set to 1)
(`blockIdx.x`, `blockIdx.y`)
 - Thread ID: 1D, 2D, or 3D **within a block**
(`threadIdx.x`, `threadIdx.y`, `threadIdx.z`)



Courtesy: NDVIA

Device Code (Kernel)

- The device code is the same for **each thread**.
- A kernel function has the prefix `__global__`, and has a *void* return type.

`__global__ void kernel1(param1, ...)`

Note: device code has no direct access to main memory.

Kernel Invocation in Host Code

***kernelName<<<#block, #thread, shared_size, s>>>
(param1, ...)***

#block: number of thread blocks in the grid

#thread: number of threads **per block**

shared_size: optional; size of shared memory **per block**, default 0.

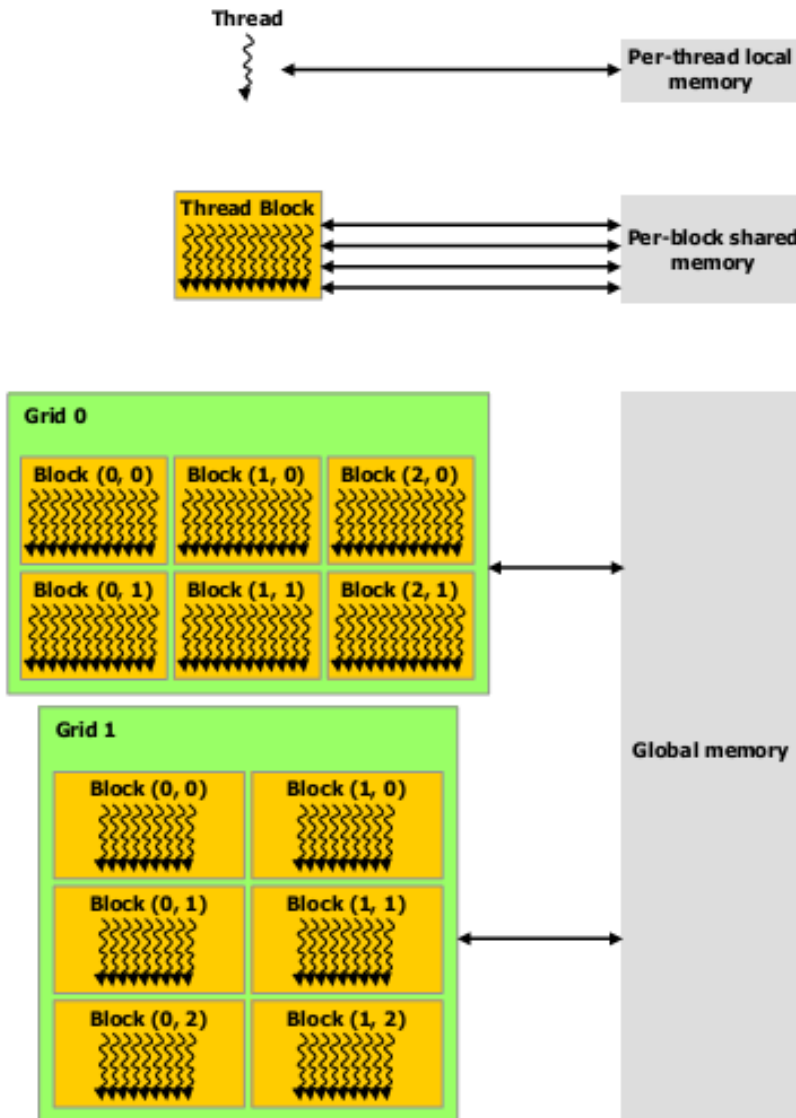
s: optional; the associated stream, default 0.

Memory Management in Host Code

- GPU memory management functions
 - GPU memory allocation:
`cudaMalloc(devPtr, size)`
`cudaFree(devPtr)`
 - Memory copy:
`cudaMemcpy(dst, src, size, direction)`
direction: cudaMemcpyHostToDevice,
cudaMemcpyDeviceToHost

Note: host code has no direct access to GPU memory.

CUDA Memory Hierarchy



- **Registers:** only available within a thread.
- **Shared memory:** accessed by threads in the same thread block.
- **Global memory:** can be accessed by all threads.

A Simple Program on the CPU

```
int main()
{
    int *h_A, *h_B, *h_C;
    int i;
    int N = 4096;
    size_t size = N * sizeof(int);

    // Allocate input vectors h_A and h_B in host memory
    h_A = (int*)malloc(size);
    h_B = (int*)malloc(size);
    h_C = (int*)malloc(size);

    /*initialize h_A and h_B here*/

    //vector Add
    for (i = 0; i < N; i++)
        h_C[i] = h_A[i] + h_B[i];

    //Free host memory
    free(h_A);
    free(h_B);
    free(h_C);

    return 0;
}
```

A recommended common practice is to name a host-resident structure with the prefix “h_” (host), and a device-resident structure with “d_” (device).

CUDA Program: Set Up on the Host

```
// Host code
int main()
{
    int *h_A, *h_B, *h_C, *d_A, *d_B, *d_C;
    int N = 4096;
    size_t size = N * sizeof(int);

    // Allocate input vectors h_A and h_B in host memory
    h_A = (int*)malloc(size);
    h_B = (int*)malloc(size);
    h_C = (int*)malloc(size);

    for (int i = 0; i < N; i++)
    {
        h_A[i] = i;
        h_B[i] = i;
    }

    // Allocate vectors in device memory
    cudaMalloc((void**)&d_A, size);
    cudaMalloc((void**)&d_B, size);
    cudaMalloc((void**)&d_C, size);

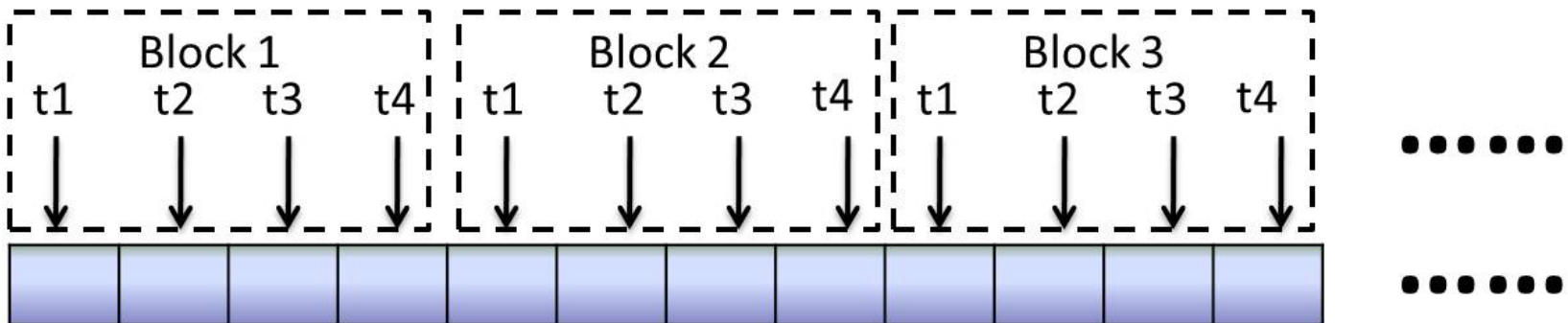
    // Copy vectors from host memory to device memory
    cudaMemcpy(d_A, h_A, size, cudaMemcpyHostToDevice);
    cudaMemcpy(d_B, h_B, size, cudaMemcpyHostToDevice);
    .
    .
    .
}
```

CUDA Program: Invoke the Kernel

```
        .  
        .  
// Invoke kernel  
int threadsPerBlock = 256;  
int blocksPerGrid = N / threadsPerBlock;  
VecAdd<<<blocksPerGrid, threadsPerBlock>>>(d_A, d_B, d_C);  
        .  
        .
```

CUDA Program: The Device Code

```
// Device code
__global__ void VecAdd(int* A, int* B, int* C)
{
    int i = blockDim.x * blockIdx.x + threadIdx.x;
    C[i] = A[i] + B[i];
}
```



CUDA Program: Wrap Up on the Host

```
        .  
        .  
    // Copy result from device memory to host memory  
    // h_C contains the result in host memory  
    cudaMemcpy(h_C, d_C, size, cudaMemcpyDeviceToHost);  
  
    //Free host memory  
    free(h_A);  
    free(h_B);  
    free(h_C);  
  
    //Free device memory  
    cudaFree(d_A);  
    cudaFree(d_B);  
    cudaFree(d_C);  
  
}
```

Another Example

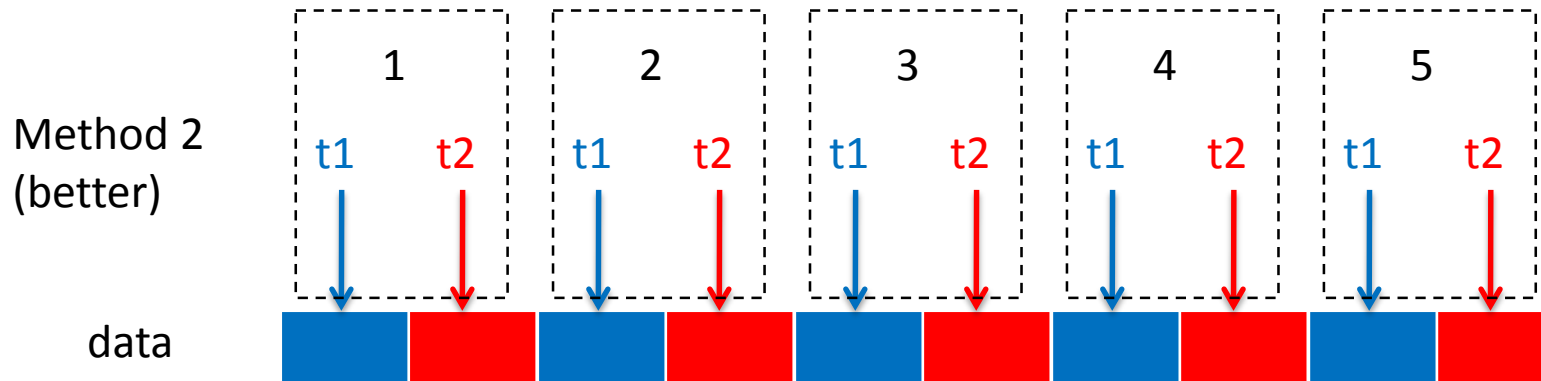
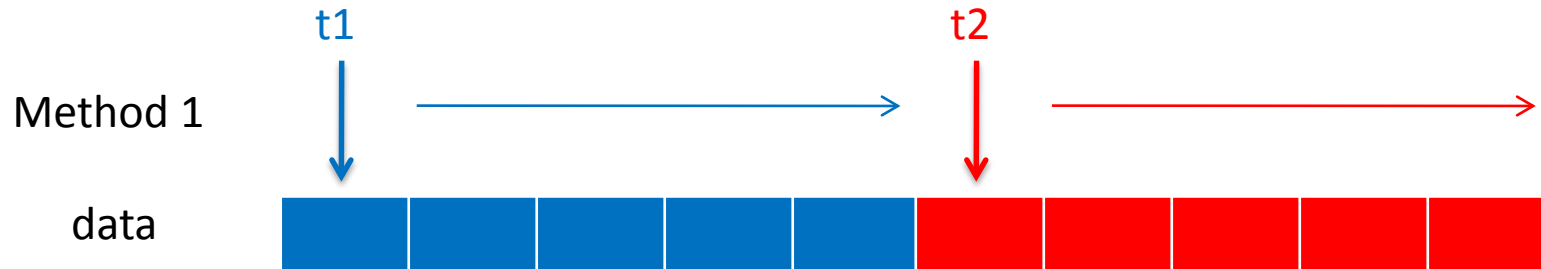
- Given an array of n elements, increment each element.
- A C program without CUDA

```
for(int i = 0; i < n; i++) {  
    h_data[i] += 1;  
}
```

The Parallelization on the GPU

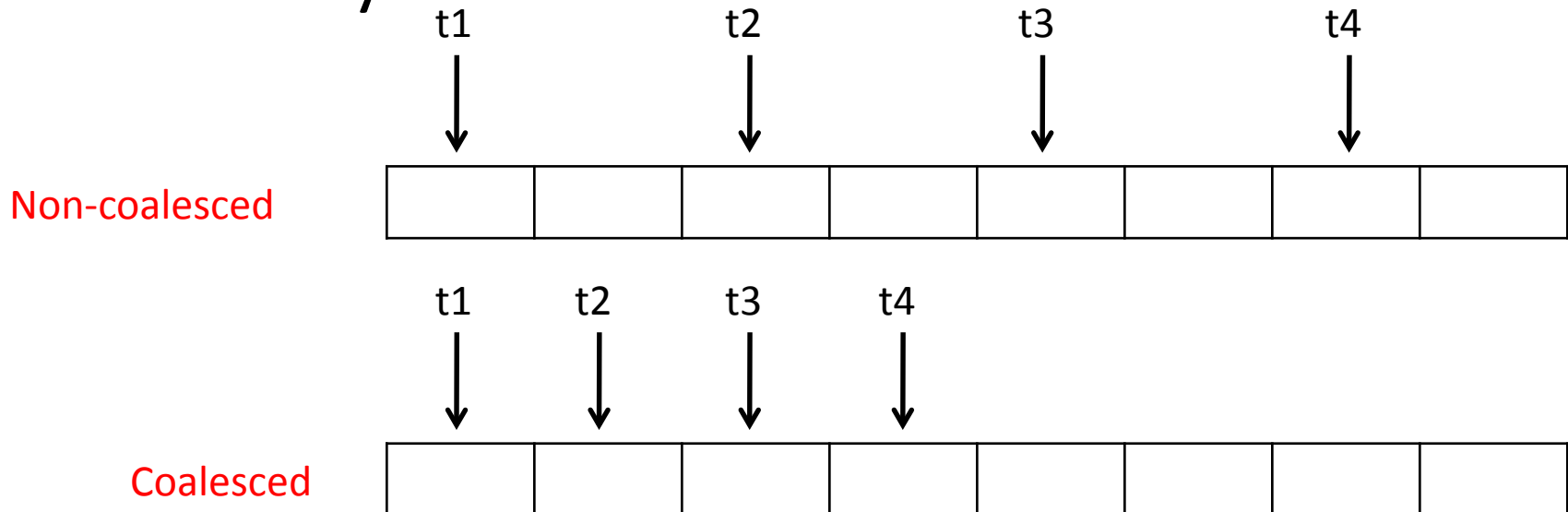
- Shall we still make one thread handle one element?
- **Maybe not...**
 - The numbers of blocks and threads for a kernel is limited, e.g., up to 65535 blocks and 1024 threads per block.
 - A suitable number of threads should balance the degree of parallelism and resource usage.
- We may need to make each thread handle multiple elements for a large number of elements.

Two Parallelization Methods



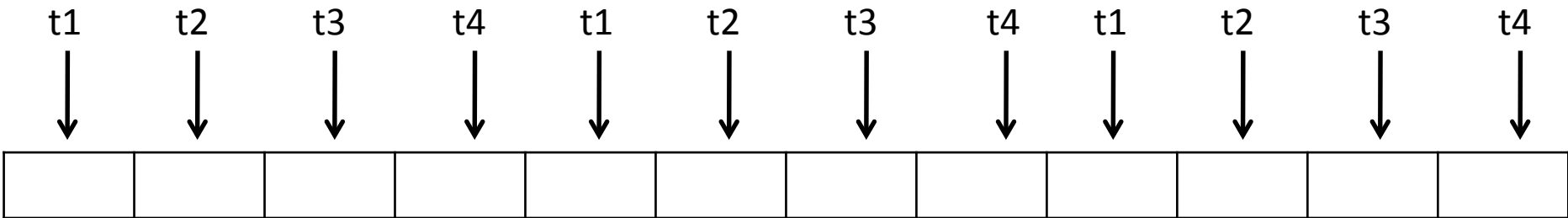
Coalesced Access

- If memory addresses accessed by threads in the same thread block are consecutive, then these memory accesses are grouped into one memory transaction.

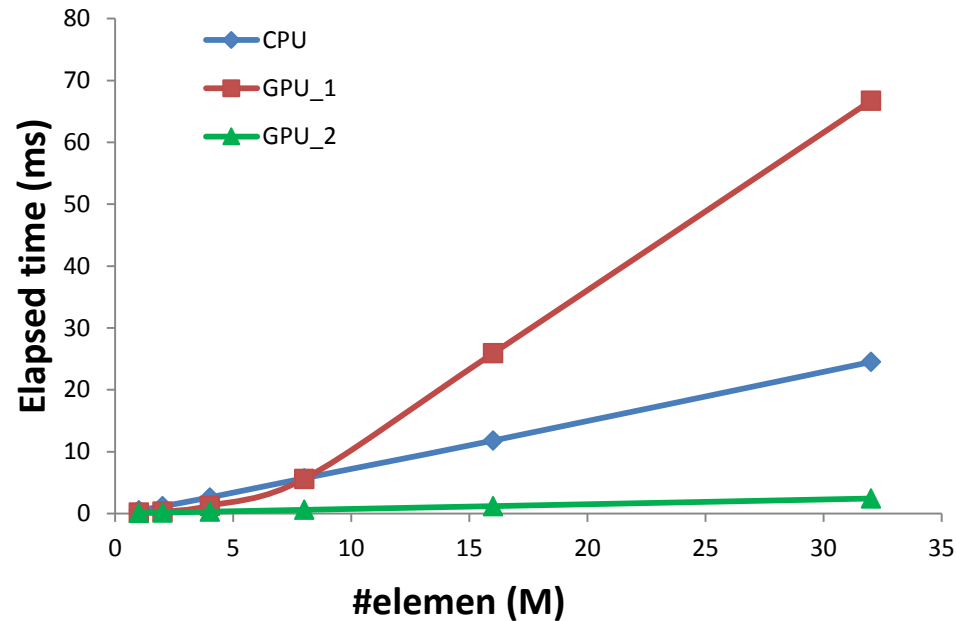


The GPU Kernel with Coalesced Access

```
__global__  
void kernel2(int* d_data, const int numElement) {  
    const int tid = blockDim.x*blockIdx.x + threadIdx.x;  
    const int nthread = blockDim.x*gridDim.x;  
  
    for(int i = tid; i < numElement; i += nthread) {  
        d_data[i] += 1;  
    }  
}
```



Performance Comparison



1. Coalesced access is crucial for utilizing the GPU memory bandwidth.
2. A badly-written GPU program may be even slower than a CPU program!

Measure Kernel Execution Time

- Kernel execution is asynchronous.
- To measure the elapsed time of a kernel, we need a synchronization between the host and device.

```
cudaEvent_t start, stop;
cudaEventCreate(&start);
cudaEventCreate(&stop);
cudaEventRecord(start, 0);
kernel1<<<1024, 512>>>(d_data);
cudaEventRecord(stop, 0);
cudaEventSynchronize(stop);
float elapsedTime;
cudaEventElapsedTime(&elapsedTime, start, stop);
printf("Kernel elapsed time: %.3f ms\n", elapsedTime);
```


Summary

- A CUDA program consists of host and device code.
- The host code is in charge of GPU memory allocation, data transfer between the GPU and the CPU, and kernel launching.
- A kernel program is executed by every thread in a grid structure.
- Coalesced access effectively utilizes GPU memory bandwidth.