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Introduction to CUDA

... curtsey of Dr. Massimo Bernaschi (CNR - http://www.iac.cnr.it/~massimo)

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What is CUDA?

- CUDA = Compute Unified Device Architecture
  - Expose general-purpose GPU computing as first-class capability
  - Retain traditional DirectX/OpenGL graphics performance

- CUDA C
  - Based on industry-standard C
  - A handful of language extensions to allow heterogeneous programs
  - Straightforward APIs to manage devices, memory, etc.

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CUDA Programming Model

- The GPU is viewed as a compute device that:
  - has its own RAM (device memory)
  - runs data-parallel portions of an application as kernels by using many threads

- GPU vs. CPU threads
  - GPU threads are extremely lightweight
  - Very little creation overhead
  - GPU needs 1000s of threads for full efficiency
  - A multi-core CPU needs only a few (basically one thread per core)

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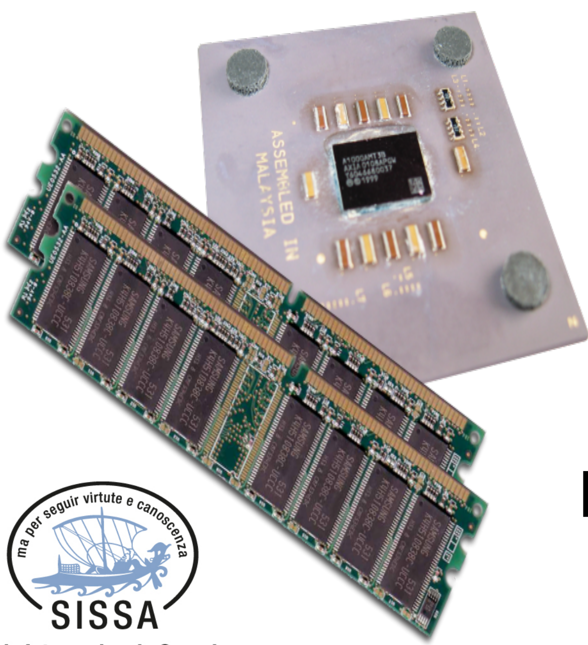
CUDA C Jargon: The Basics

- The CPU and its memory (host memory)
- The GPU and its memory (device memory)



Host

Device

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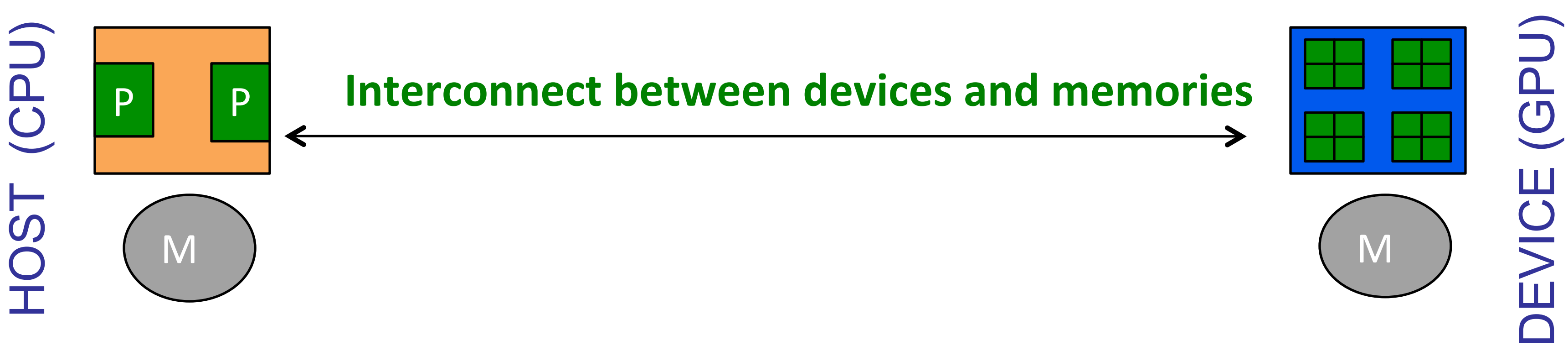
What Programmer Expresses in CUDA



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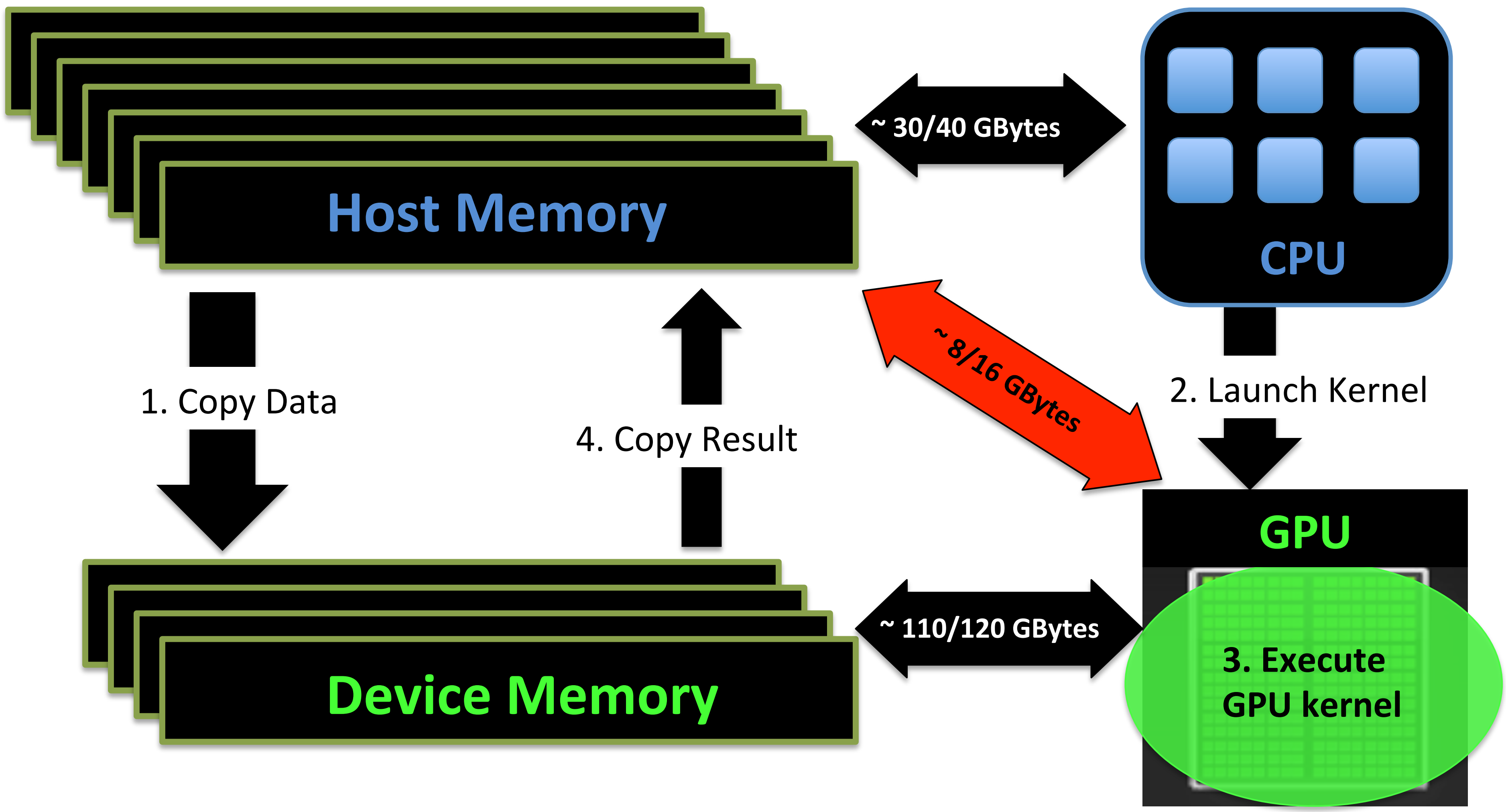

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What Programmer Expresses in CUDA

- Computation partitioning (where does computation occur?)
  - Declarations on functions __host__, __global__, __device__
  - Mapping of thread programs to device: **compute <<<gs, bs>>>(<args>)**
- Data partitioning (where does data reside, who may access it and how?)
  - Declarations on data __shared__, __device__, __constant__, …
- Data management and orchestration
  - Copying to/from host:
    e.g., cudaMemcpy(h_obj,d_obj, size, cudaMemcpyDevicetoHost)
- Concurrency management
  - *e.g.* __synchthreads()

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Hello, World!

```
int main( void ) {
   printf( "Hello, World!\n" );
   return 0;
}
```

- To compile: **nvcc –o hello_world hello_world.cu**
- To execute: **./hello_world**
- This basic program is just standard C that runs on the *host*
- NVIDIA's compiler (`nvcc`) will not complain about CUDA programs with no *device* code
- At its simplest, CUDA C is just C!

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Hello, World! with Device Code

```
__global__ void kernel( void ) {
}

int main( void ) {

   kernel<<<1,1>>>();
   printf( "Hello, World!\n" );
   return 0;
}
```

To compile: **nvcc –o simple_kernel simple_kernel.cu**

To execute: **./simple_kernel**

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Hello, World! with Device Code

```
__global__ void kernel( void ) {
}
```

- CUDA C keyword **`__global__`** indicates that a function
  - Runs on the device
  - Called from host code
- **`nvcc`** splits source file into host and device components
  - NVIDIA's compiler handles device functions like **`kernel`**`()`
  - Standard host compiler handles host functions like **`main`**`()`
    - `gcc, icc,` …
    - **Microsoft Visual C**

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Hello, World! with Device Code

```
int main( void ) {
    kernel<<< 1, 1 >>>();
    printf( "Hello, World!\n" );
    return 0;
}
```

- Triple angle brackets mark a call from *host* code to *device* code
  - A “kernel launch” in CUDA jargon
  - We’ll discuss the parameters inside the angle brackets later
- This is all that’s required to execute a function on the GPU!

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A More Complex Example

- A kernel to add two integers:

```
__global__ void add( int *a, int *b, int *c ) {
        *c = *a + *b;
}
```

- As before, `__global__` is a CUDA C keyword meaning
  - `add()` will execute on the device
  - `add()` will be called from the host

A More Complex Example

- Notice that now we use ***pointers*** for all our variables:

```
__global__ void add( int *a, int *b, int *c ) {
        *c = *a + *b;
}
```

- **`add()`** runs on the device…so **`a`**, **`b`**, and **`c`** must point to device memory
- How do we allocate memory on the GPU?

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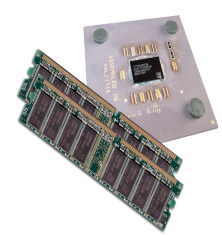
Memory Management

- Up to CUDA 4.0 host and device memory were distinct entities from the programmers' viewpoint
  - Device pointers point to GPU memory
    - May be passed to and from host code
    - (In general) May not be dereferenced from host code
  - Host pointers point to CPU memory
    - May be passed to and from device code
    - (In general) May not be dereferenced from device code



Starting on CUDA 4.0 there is a **Unified Virtual Addressing** feature.

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Memory Management

- Basic CUDA API for dealing with device memory
  - **cudaMalloc**(&p, size), **cudaFree**(p), **cudaMemcpy**(t, s, size, direction)
  - Similar to their C equivalents: **malloc**(), **free**(), **memcpy**()

pointer to pointer

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```
int main( void ) {
    int a, b, c;                // host copies of a, b, c
    int *dev_a, *dev_b, *dev_c; // device copies of a, b, c
    int size = sizeof( int );   // we need space for an integer
    // allocate device copies of a, b, c
    cudaMalloc( (void**)&dev_a, size );
    cudaMalloc( (void**)&dev_b, size );
    cudaMalloc( (void**)&dev_c, size );
    a = 2;
    b = 7;
// copy inputs to device
    cudaMemcpy( dev_a, &a, size, cudaMemcpyHostToDevice );
    cudaMemcpy( dev_b, &b, size, cudaMemcpyHostToDevice );
    // launch add() kernel on GPU, passing parameters
    add<<< 1, 1 >>>( dev_a, dev_b, dev_c );
    // copy device result back to host copy of c
    cudaMemcpy( &c, dev_c, size, cudaMemcpyDeviceToHost );
    cudaFree( dev_a ); cudaFree( dev_b ); cudaFree( dev_c )
    return 0;
}
```

```
#include "cuPrintf.cu"

__global__ void testKernel(int param){
   cuPrintf("Param value: %d\n", param);
}

int main(void){
   // initialize cuPrintf
   cudaPrintfInit();
   int a = 456;
   testKernel<<<4,1>>>(a);
   // display the device's greeting
   cudaPrintfDisplay();
   // clean up after cuPrintf
   cudaPrintfEnd();
}  // compile with nvcc -o test.x test.cu -I$CUDADIR/samples/0_Simple/simplePrintf
```

Also simple printf() works!!!

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CUDA Error Checking

- CUDA host function calls usually return a value of type **cudaError_t**

```
cudaError_t cudaMalloc (void **devPtr, size_t size)
```

- Example: to check if device allocation was successful

```
cudaError_t error;
[...]
error = cudaMalloc(&d_a, memSize);
if (error != cudaSuccess)
{
    printf("Error in device allocation: %s\n",! ! ! ! cudaGetErrorString(error));
}
```

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CUDA Error Checking

- Kernels can't have a return value, so cudaGetLastError() is used

```
cudaError_t error;
[...]
myKernel<<<1, 1>>>(a_d);
error = cudaGetLastError();
if (error != cudaSuccess)
{
    printf("Error in Kernel  execution: %s\n", cudaGetErrorString(error) );
}
```

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Parallel Programming in CUDA C

- But wait…GPU computing is about **massive** parallelism
- So how do we run code ***in parallel*** on the device?
- Solution lies in the parameters between the triple angle brackets:

```
add<<< 1, 1 >>>( dev_a, dev_b, dev_c );

add<<< N, 1 >>>( dev_a, dev_b, dev_c );
```

- Instead of executing `add()` once, `add()` executed **N** times in parallel

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Parallel Programming in CUDA C

- With `add()` running in parallel…let's do *vector* addition
- Terminology: Each parallel invocation of `add()` referred to as a ***block***
- Kernel can refer to its block's index with the variable `blockIdx.x`
- Each block adds a value from `a[]` and `b[]`, storing the result in `c[]`:

```
__global__ void add( int *a, int *b, int *c ) {
    c[blockIdx.x] = a[blockIdx.x] + b[blockIdx.x];
}
```

- By using `blockIdx.x` to index arrays, each block handles a different index
- `blockIdx.x` is the first example of a CUDA predefined variable.

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Parallel Programming in CUDA C

- We write this code:

```
__global__ void add( int *a, int *b, int *c ) {
    c[blockIdx.x] = a[blockIdx.x] + b[blockIdx.x];
}
```

- This is what runs in parallel on the device:

Block 0	Block 1
`c[0]=a[0]+b[0];`	`c[1]=a[1]+b[1];`
Block 2	**Block 3**
`c[2]=a[2]+b[2];`	`c[3]=a[3]+b[3];`

Parallel Addition: `main()`

```
#define N  512
int main( void ) {
    int *a, *b, *c;                 // host copies of a, b, c
    int *dev_a, *dev_b, *dev_c;     // device copies of a, b, c
    int size = N * sizeof( int );   // we need space for 512
                                    // integers

    // allocate device copies of a, b, c
    cudaMalloc( (void**)&dev_a, size );
    cudaMalloc( (void**)&dev_b, size );
    cudaMalloc( (void**)&dev_c, size );

    a = (int*)malloc( size );
    b = (int*)malloc( size );
    c = (int*)malloc( size );

    random_ints( a, N );
    random_ints( b, N );
```

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Parallel Addition: `main()` (cont)

```
    // copy inputs to device
    cudaMemcpy( dev_a, a, size, cudaMemcpyHostToDevice );
    cudaMemcpy( dev_b, b, size, cudaMemcpyHostToDevice );

    // launch add() kernel with N parallel blocks
    add<<< N, 1 >>>( dev_a, dev_b, dev_c );

    // copy device result back to host copy of c
    cudaMemcpy( c, dev_c, size,   cudaMemcpyDeviceToHost );

    free( a ); free( b ); free( c );
    cudaFree( dev_a );
    cudaFree( dev_b );
    cudaFree( dev_c );
    return 0;
}
```

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Review

- Difference between “host” and “device”
  - Host = CPU
  - Device = GPU

- Using `__global__` to declare a function as device code
  - Runs on device
  - Called from host

- Passing parameters from host code to a device function

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Review (cont)

- Basic device memory management
  - **`cudaMalloc`**`()`
  - **`cudaMemcpy`**`()`
  - **`cudaFree`**`()`

- Launching parallel kernels
  - Launch **`N`** copies of **`add()`** with: **`add <<< N, 1 >>>();`**
  - **`blockIdx.x`** allows to access block's index

Exercise: look at, compile and run the *add_simple_blocks.cu* code

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Threads

- Terminology: A block can be split into parallel ***threads***
- Let's change vector addition to use parallel threads instead of parallel blocks:

```
__global__ void add( int *a, int *b, int *c ) {
c[threadIdx.x] = a[threadIdx.x]+ b[threadIdx.x];
}
```

- We use `threadIdx.x` instead of `blockIdx.x` in `add()`
- `main()` will require one change as well…

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Parallel Addition (Threads): `main()`

```
#define N  512
int main( void ) {
    int *a, *b, *c;                    // host copies of a, b, c
    int *dev_a, *dev_b, *dev_c;        // device copies of a, b, c
    int size = N * sizeof( int );      // we need space for 512
                                       // integers

    // allocate device copies of a, b, c
    cudaMalloc( (void**)&dev_a, size );
    cudaMalloc( (void**)&dev_b, size );
    cudaMalloc( (void**)&dev_c, size );

    a = (int*)malloc( size );
    b = (int*)malloc( size );
    c = (int*)malloc( size );

    random_ints( a, N );
    random_ints( b, N );
```

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Parallel Addition (Threads): `main()` (cont)

```
    // copy inputs to device
    cudaMemcpy( dev_a, a, size, cudaMemcpyHostToDevice );
    cudaMemcpy( dev_b, b, size, cudaMemcpyHostToDevice );

    // launch add() kernel with N parallel threads
    add<<< 1, N >>>( dev_a, dev_b, dev_c );

    // copy device result back to host copy of c
    cudaMemcpy( c, dev_c, size,   cudaMemcpyDeviceToHost );

    free( a ); free( b ); free( c );
    cudaFree( dev_a );
    cudaFree( dev_b );
    cudaFree( dev_c );
    return 0;
}
```

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Using Threads *<u>And</u>* Blocks

- We've seen parallel vector addition using
  - Many blocks with 1 thread apiece
  - 1 block with many threads

- Let's adapt vector addition to use lots of ***both*** blocks and threads

- After using threads and blocks together, we'll talk about ***why*** threads

- First let's discuss data indexing…

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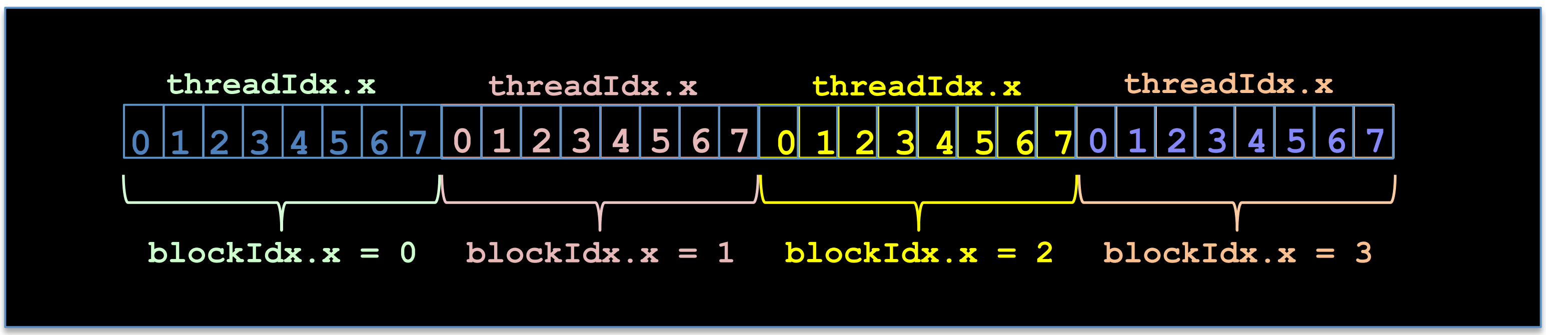
Indexing Arrays With Threads & Blocks

- No longer as simple as just using **`threadIdx.x`** or **`blockIdx.x`** as indices
- To index array with 1 thread per entry (using 8 threads/block)



- If we have **`M`** threads/block, a unique array index for each entry is given by

```
int index = threadIdx.x + blockIdx.x * M;

int index =     x       +     y      * width;
```

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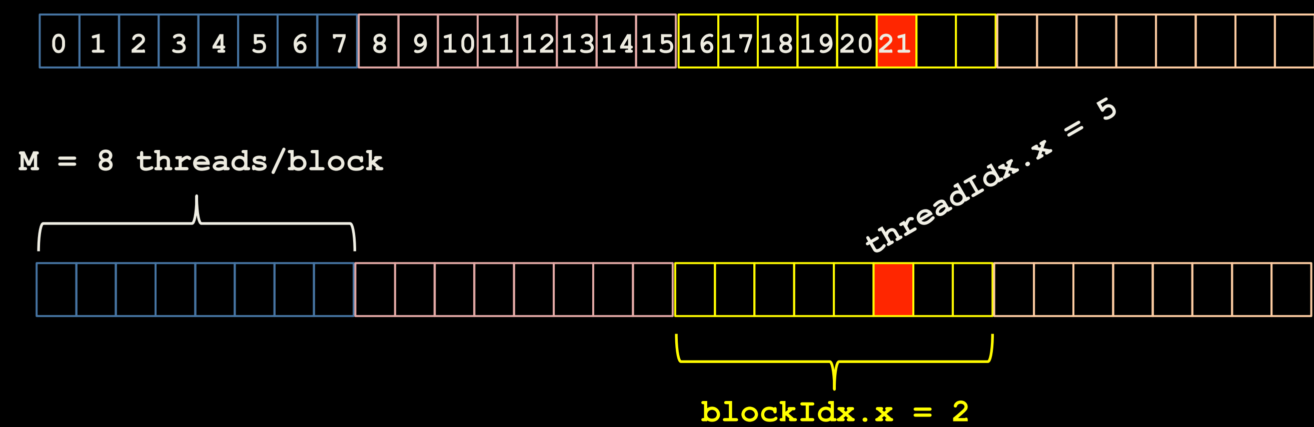
Indexing Arrays: Example

- In this example, the **red** entry would have an index of 21:




```
int index = threadIdx.x + blockIdx.x * M;
          =      5      +      2     * 8;
          = 21;
```

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Indexing Arrays: other examples (4 blocks with 4 threads *per* block)

```
__global__ void kernel( int *a )
{
    int idx = blockIdx.x*blockDim.x + threadIdx.x;
    a[idx] = 7;
}                               Output: 7 7 7 7 7 7 7 7 7 7 7 7 7 7 7 7


__global__ void kernel( int *a )
{
    int idx = blockIdx.x*blockDim.x + threadIdx.x;
    a[idx] = blockIdx.x;
}
                                Output: 0 0 0 0 1 1 1 1 2 2 2 2 3 3 3 3


__global__ void kernel( int *a )
{
    int idx = blockIdx.x*blockDim.x + threadIdx.x;
    a[idx] = threadIdx.x;
                                Output: 0 1 2 3 0 1 2 3 0 1 2 3 0 1 2 3
}
```

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Addition with Threads and Blocks

- `blockDim.x` is a built-in variable for threads per block:

```
int index = threadIdx.x + blockIdx.x * blockDim.x;
```

- `gridDim.x` is a built-in variable for blocks in a grid;

- A combined version of our vector addition kernel to use blocks *and* threads:

```
__global__ void add( int *a, int *b, int *c ) {
int index = threadIdx.x + blockIdx.x * blockDim.x;
     c[ index ] = a[ index ] + b[ index ];
}
```

- So what changes in `main()` when we use both blocks and threads?

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Parallel Addition (Bloks/Threads): main()

```
#define N  (2048 * 2048)
#define THREADS_PER_BLOCK 512
int main( void ) {
    int *a, *b, *c;                 // host copies of a, b, c
    int *dev_a, *dev_b, *dev_c;     // device copies of a, b, c
    int size = N * sizeof( int ); // we need space for N integers

    // allocate device copies of a, b, c
    cudaMalloc( (void**)&dev_a, size );
    cudaMalloc( (void**)&dev_b, size );
    cudaMalloc( (void**)&dev_c, size );

    a = (int*)malloc( size );
    b = (int*)malloc( size );
    c = (int*)malloc( size );

    random_ints( a, N );
    random_ints( b, N );
```

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Parallel Addition (Threads): `main()` (cont)

```
    // copy inputs to device
    cudaMemcpy( dev_a, a, size, cudaMemcpyHostToDevice );
    cudaMemcpy( dev_b, b, size, cudaMemcpyHostToDevice );

    // launch add() kernel with blocks and threads
  add<<< N/THREADS_PER_BLOCK, THREADS_PER_BLOCK >>>(dev_a, dev_b, dev_c);

    // copy device result back to host copy of c
    cudaMemcpy( c, dev_c, size,   cudaMemcpyDeviceToHost );

    free( a ); free( b ); free( c );
    cudaFree( dev_a );
    cudaFree( dev_b );
    cudaFree( dev_c );
    return 0;
}
```

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Exercises

- Array reversal: fill an input array d_in and save the content in revers order into d_out. The revers is performed into the GPU.
  - d_in is [100, 110, 200, 220, 300]
    then d_out must be [300, 220, 200, 110, 100]
  - blockDim.x is the number of threads per block
  - gridDim.x is the number of blocks in a grid
- Implement a Matrix Transpose using threads and blocks
- Implement a Matrix Multiplication for Matrix sizes 2048^2.
  Use max 512 threads x block.