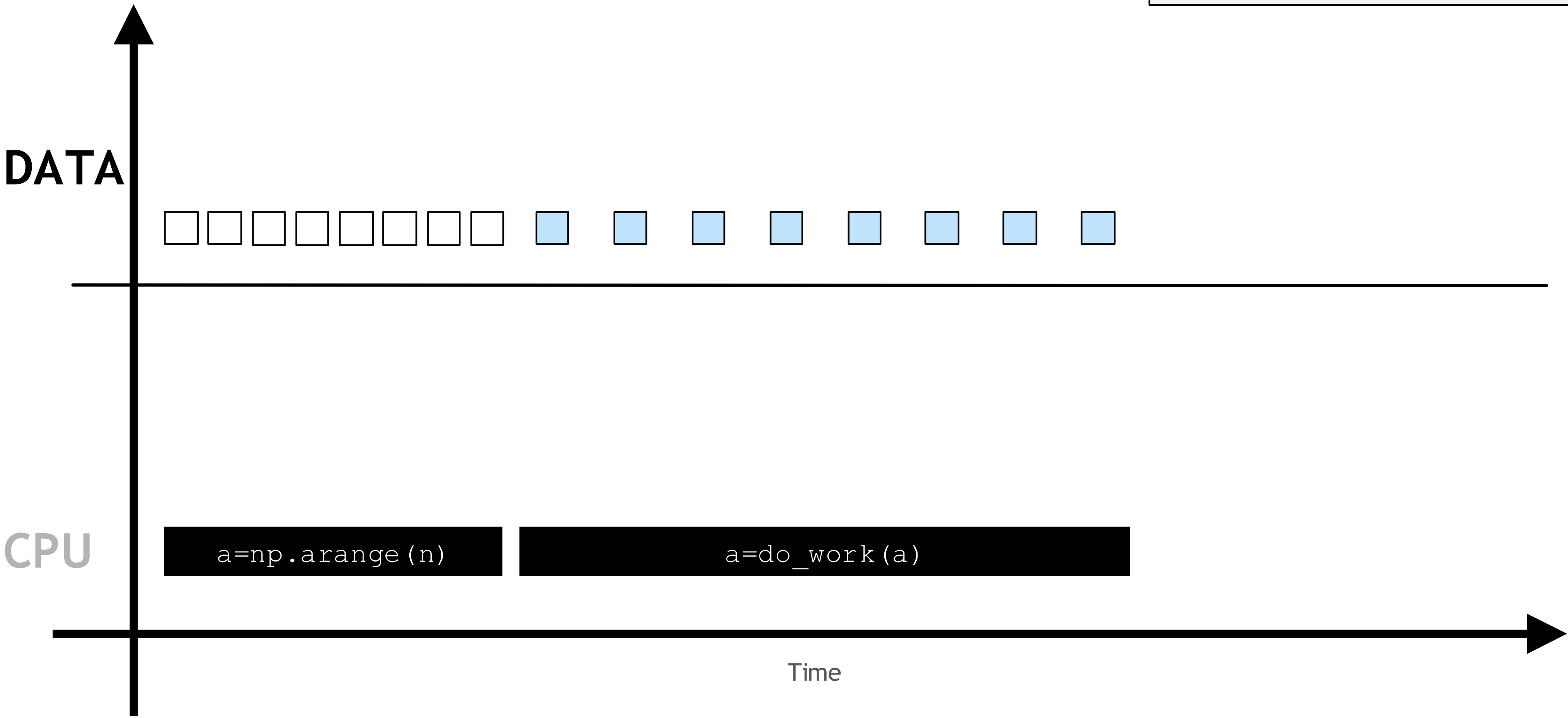
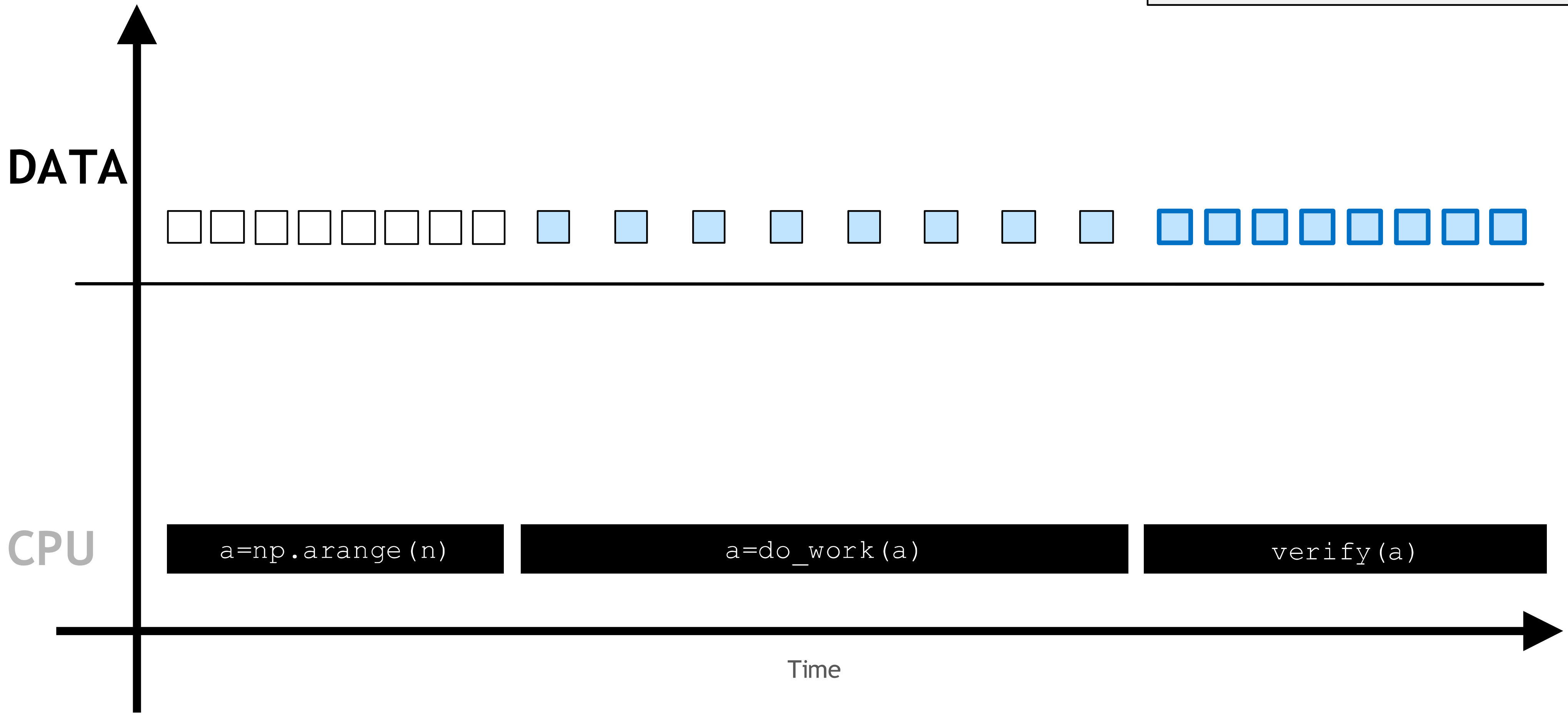
GPU-accelerated vs. CPU-only Applications

In **CPU-only applications** data is allocated on the CPU

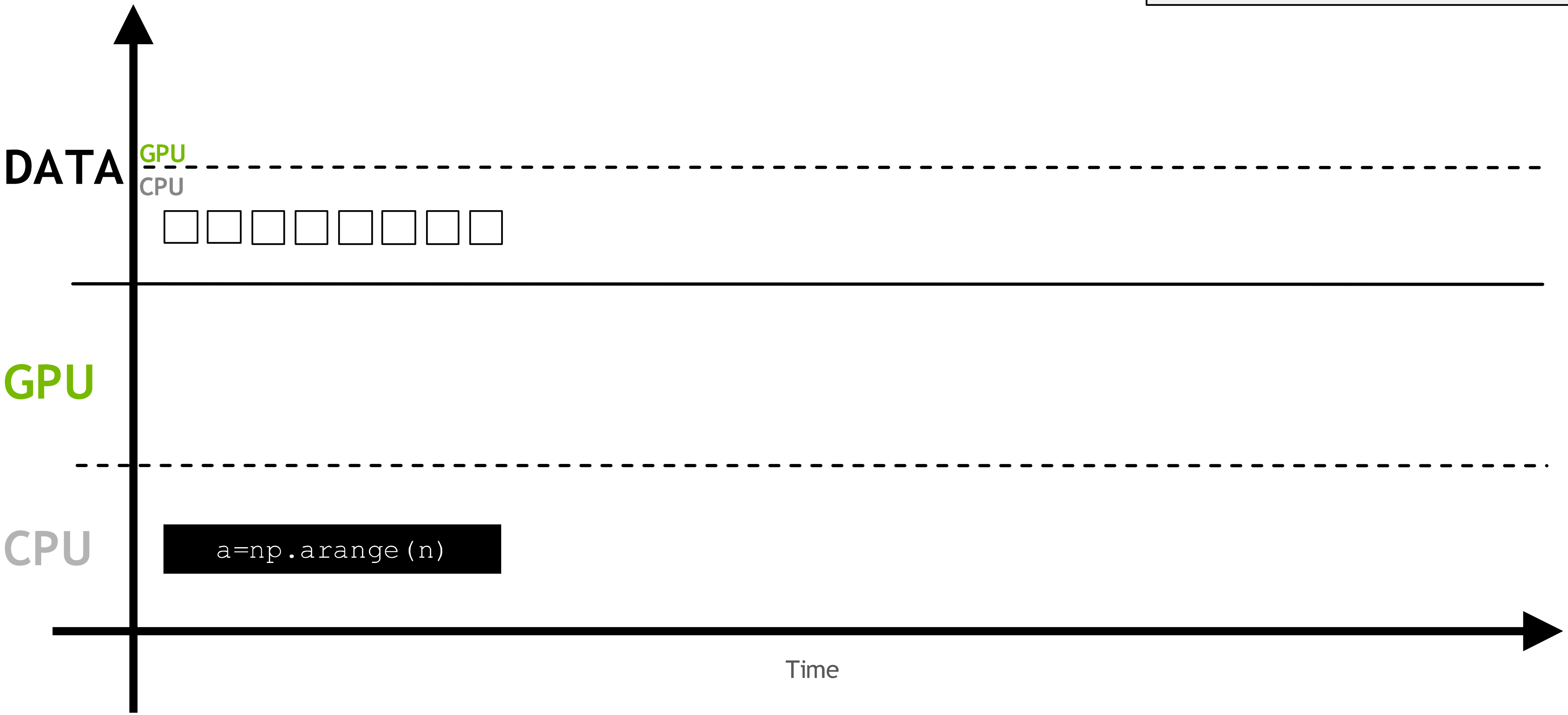
…and all work is performed serially on the CPU



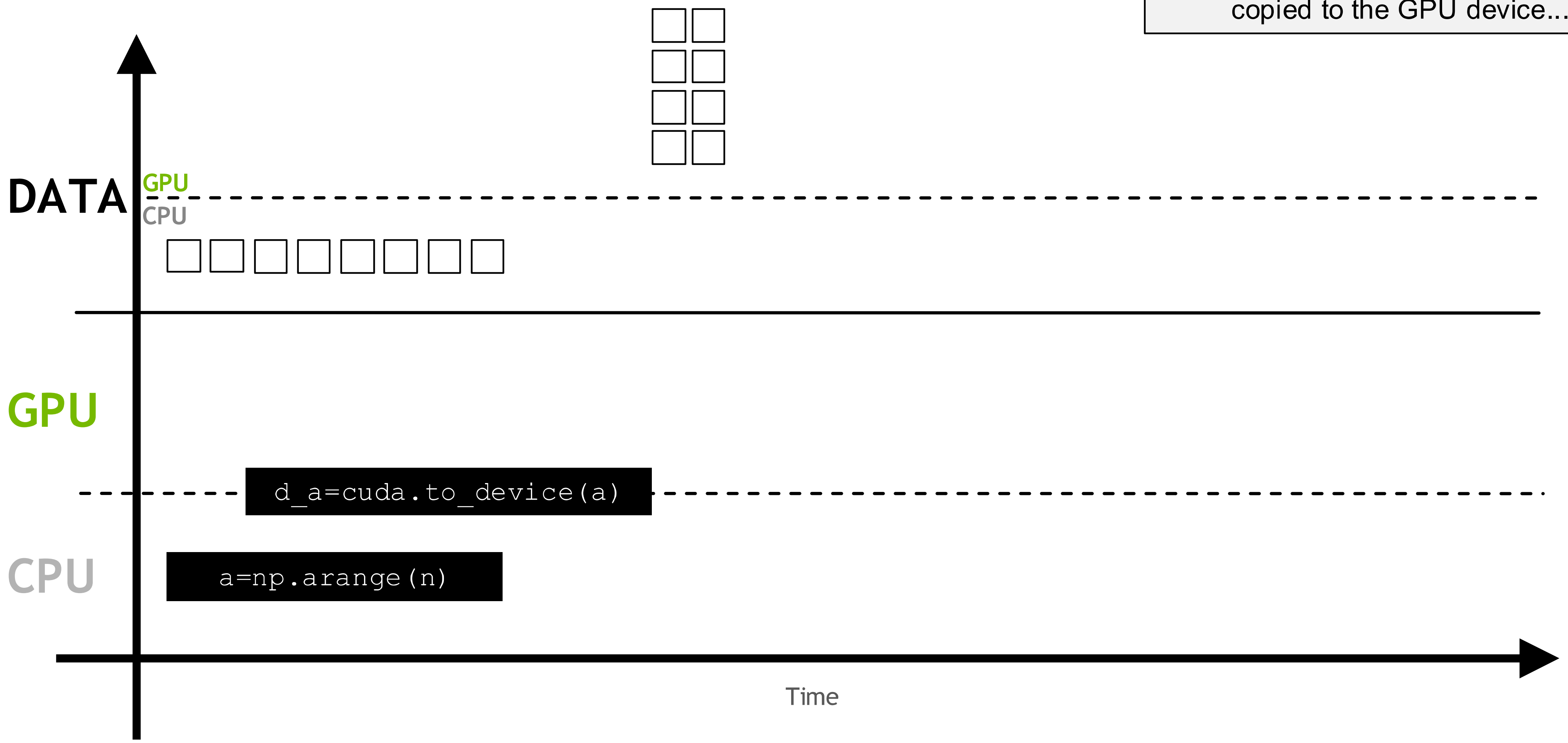
...and all work is performed serially on the CPU



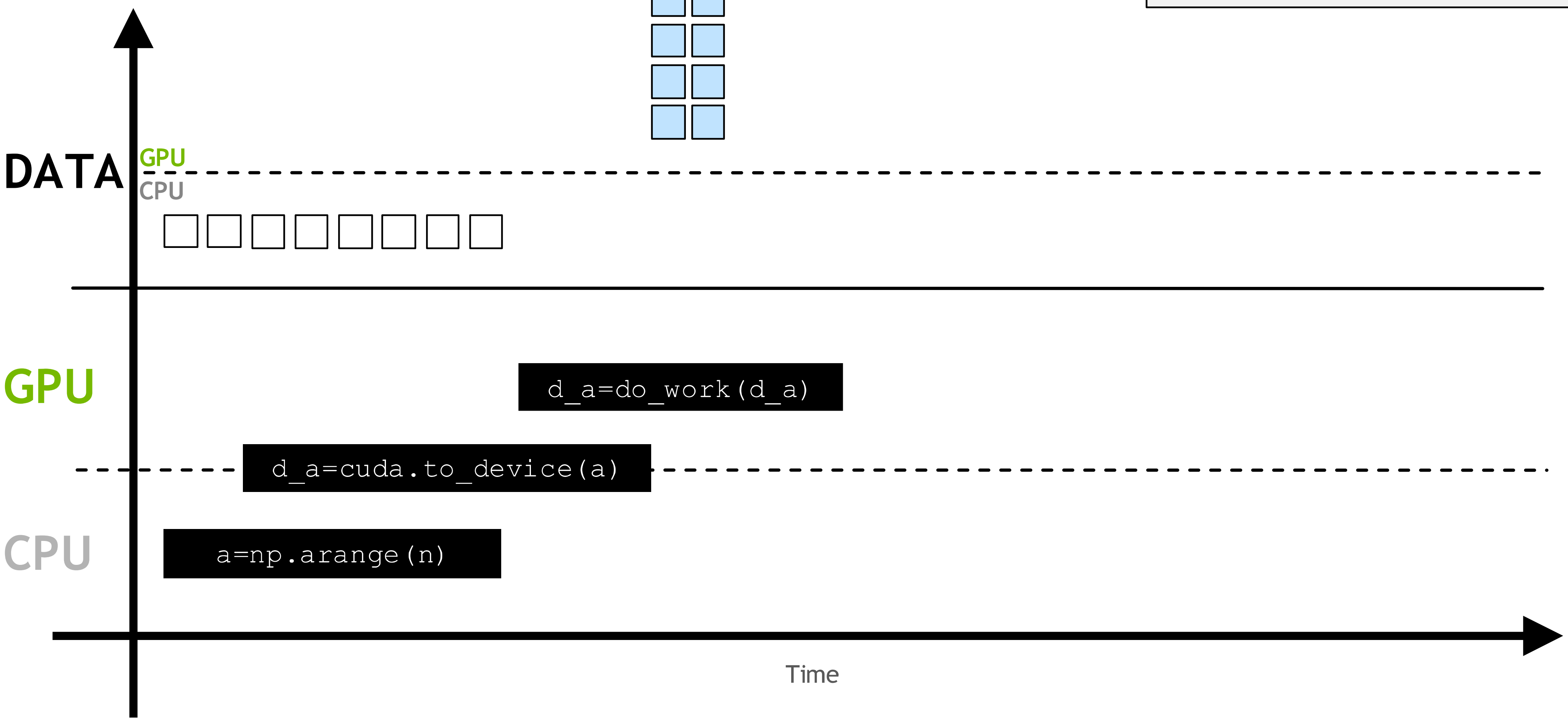
In **accelerated applications** there is both host and device memory.



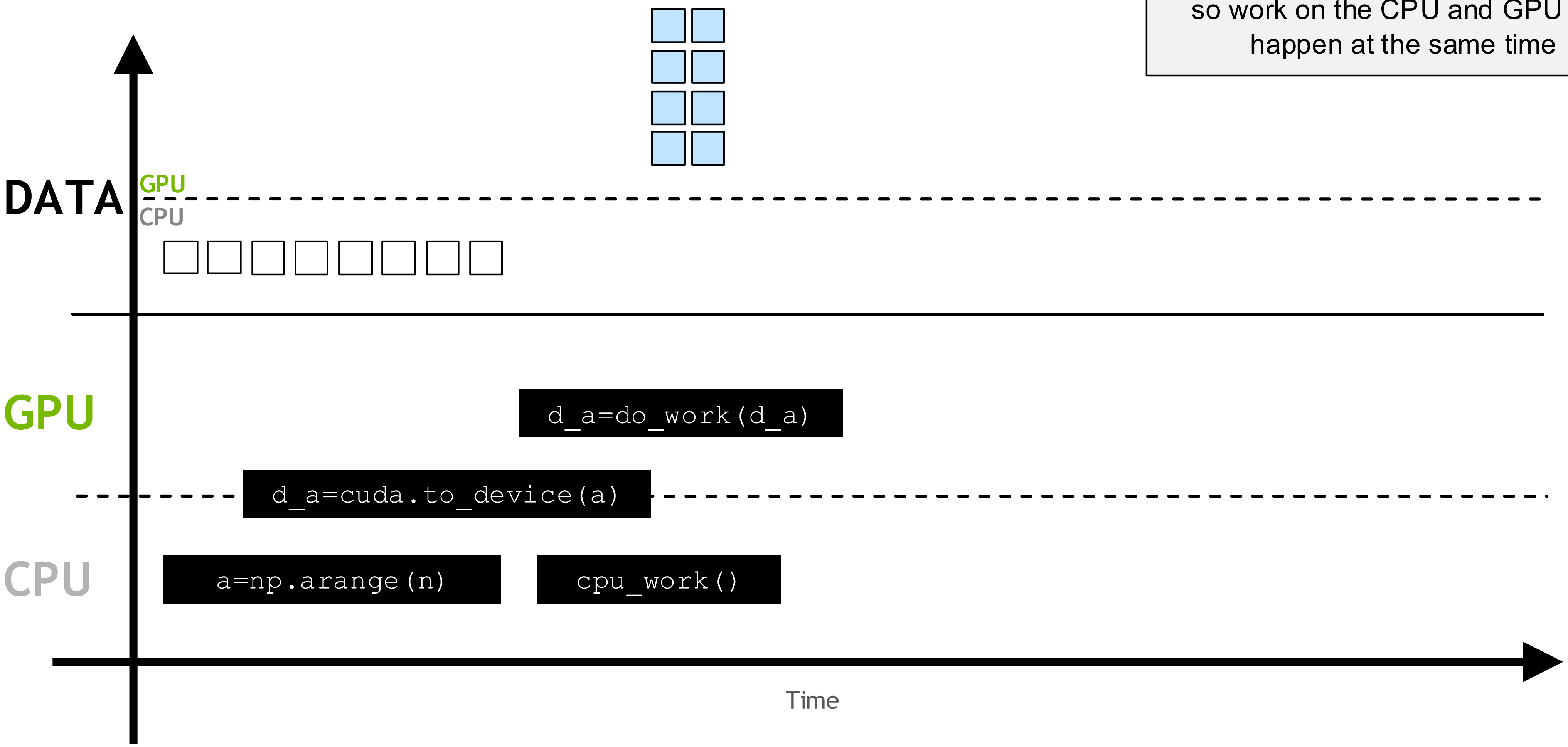
Data initialized on the CPU can be copied to the GPU device...



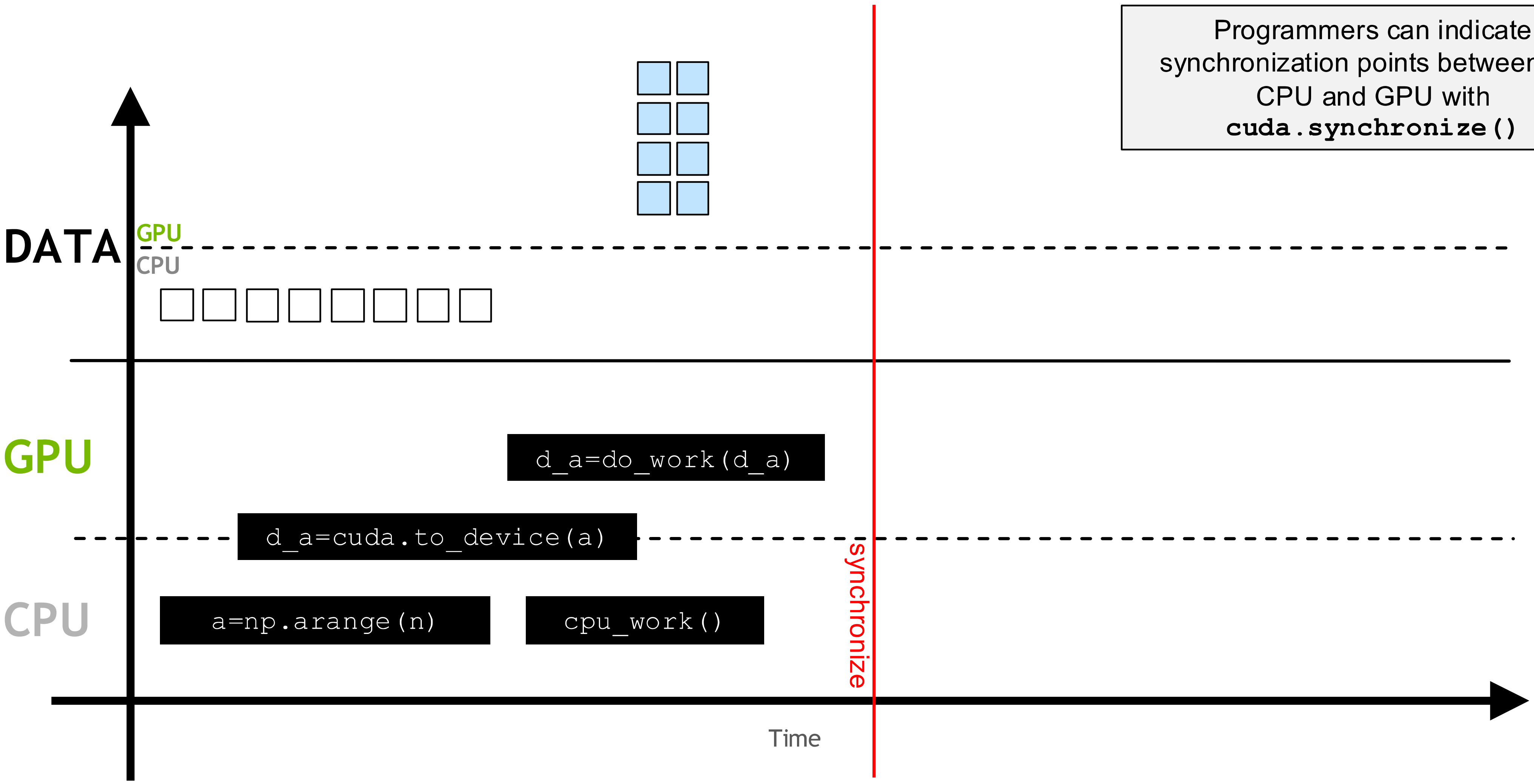
… where it can be worked on in parallel



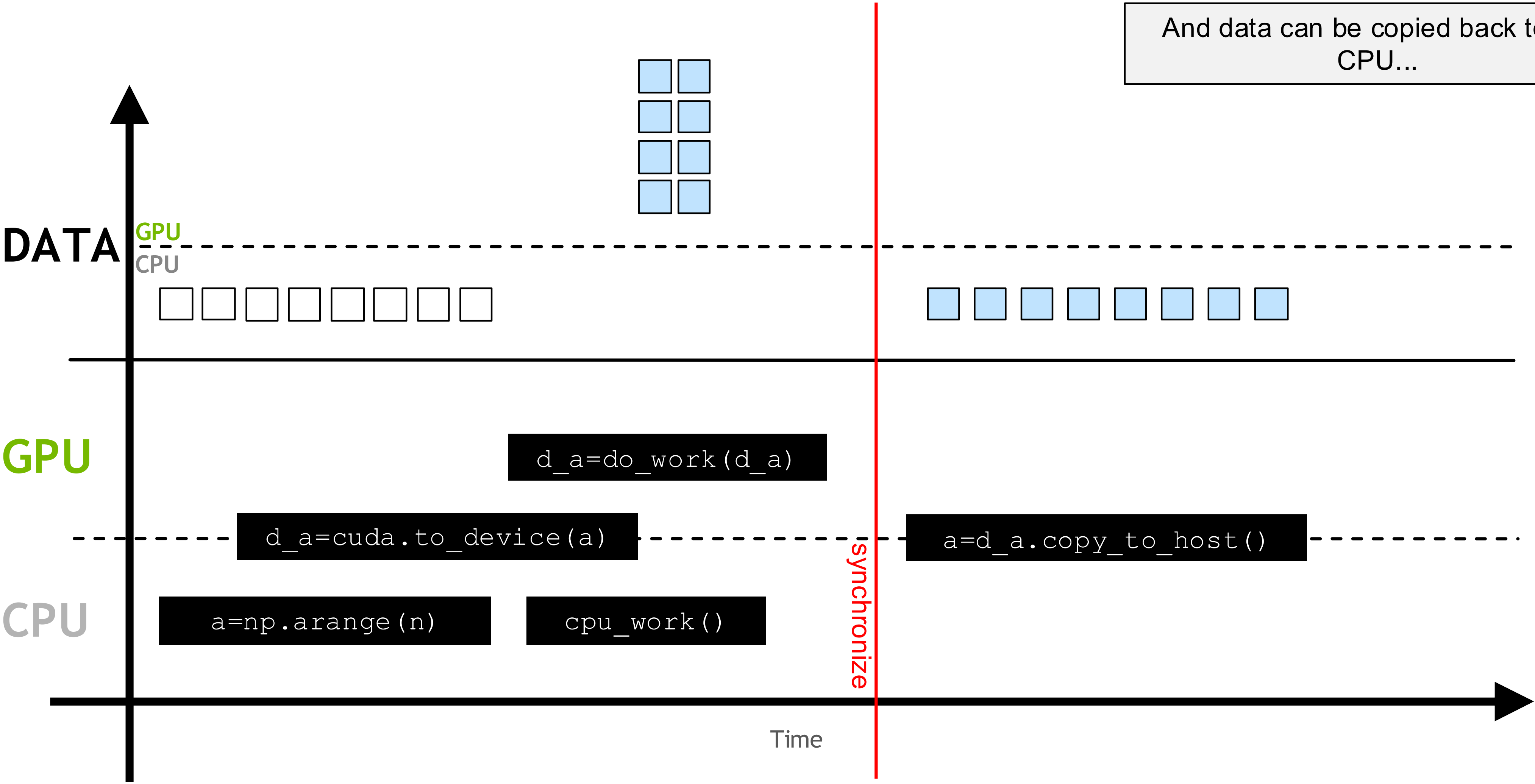
GPU work is asynchronous to the host, so work on the CPU and GPU can happen at the same time

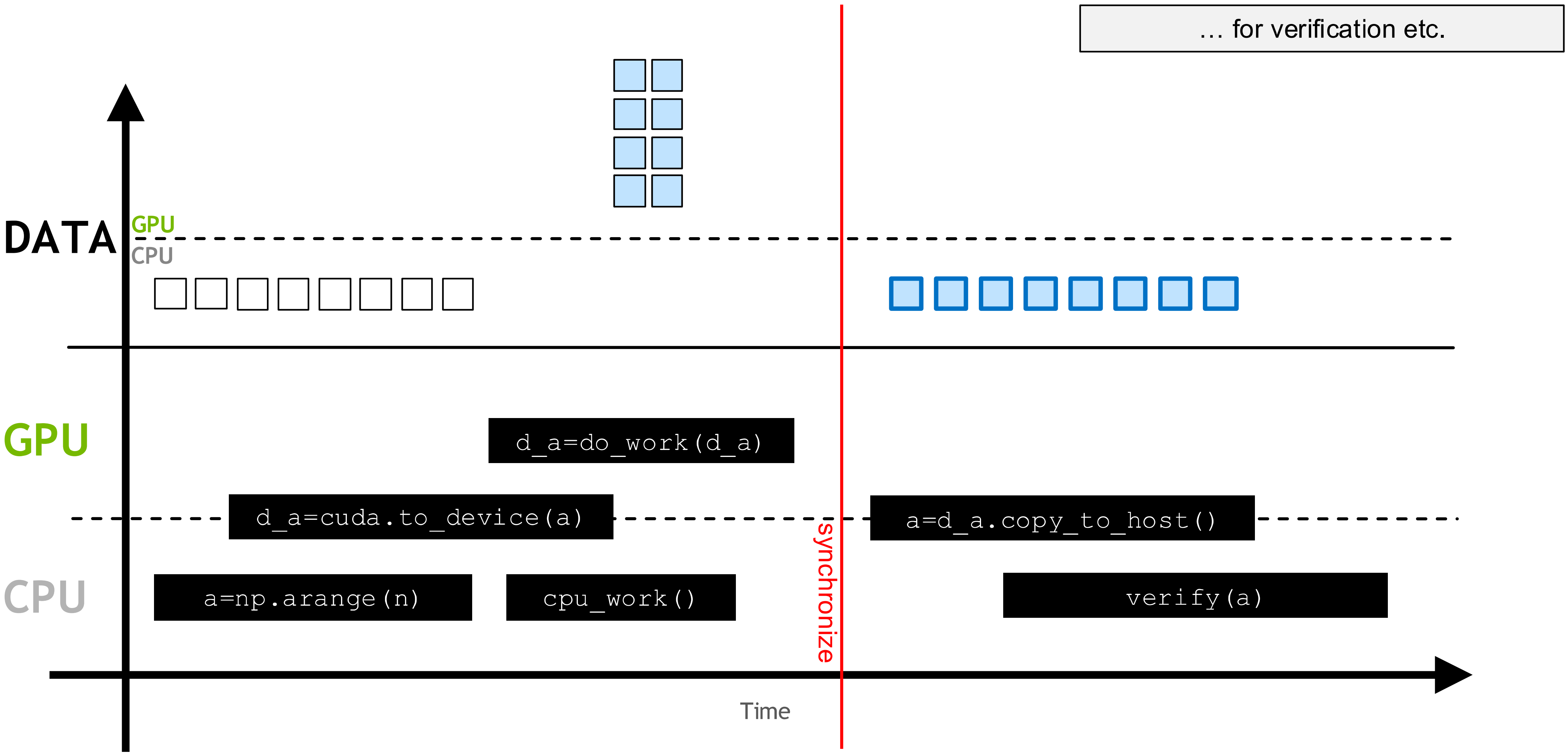


Programmers can indicate synchronization points between the CPU and GPU with **`cuda.synchronize()`**



And data can be copied back to the CPU...

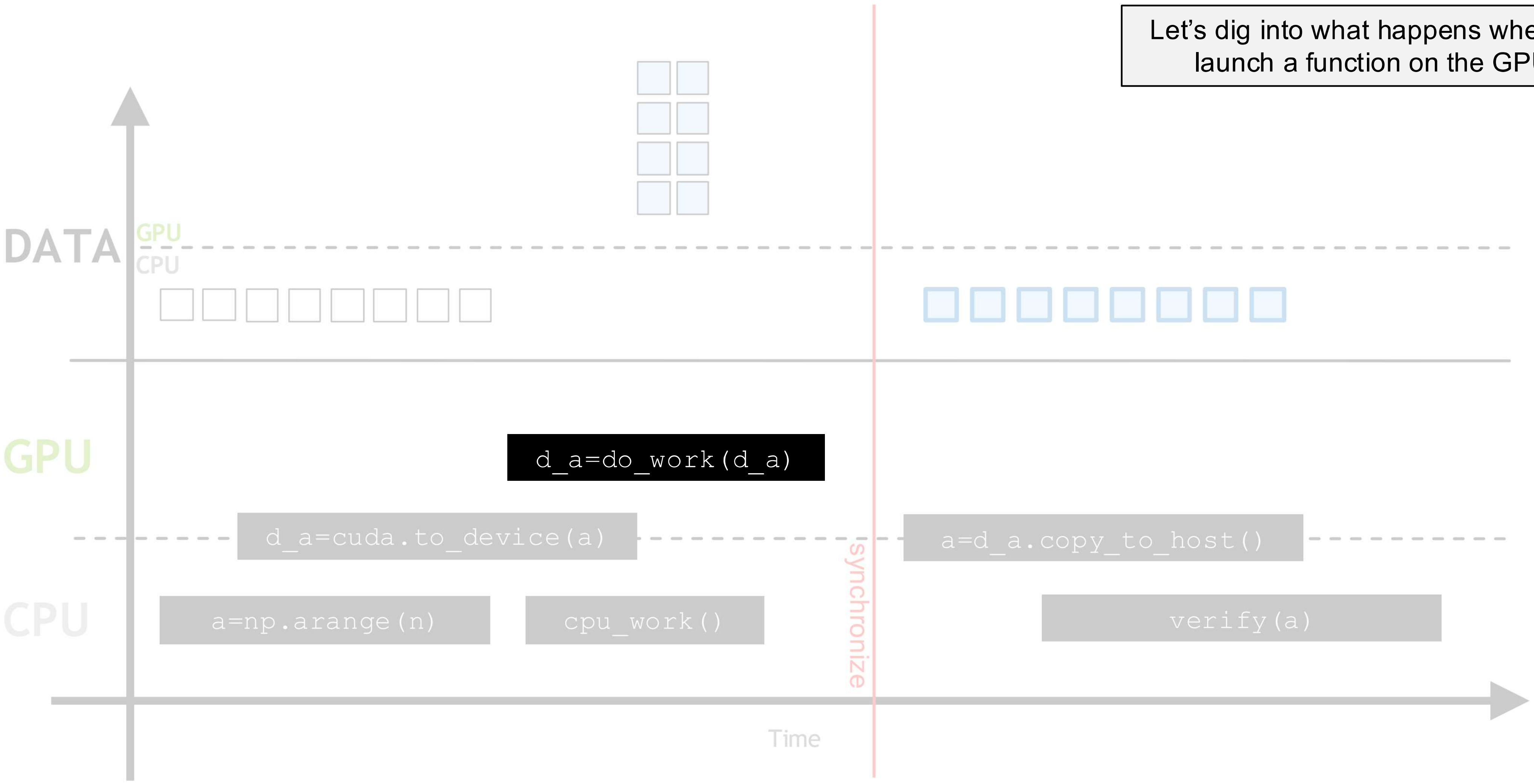




... for verification etc.
DATA
GPU
CPU
GPU
CPU
d_a=do_work(d_a)
d_a=cuda.to_device(a)
a=d_a.copy_to_host()
a=np.arange(n)
cpu_work()
verify(a)
synchronize
Time

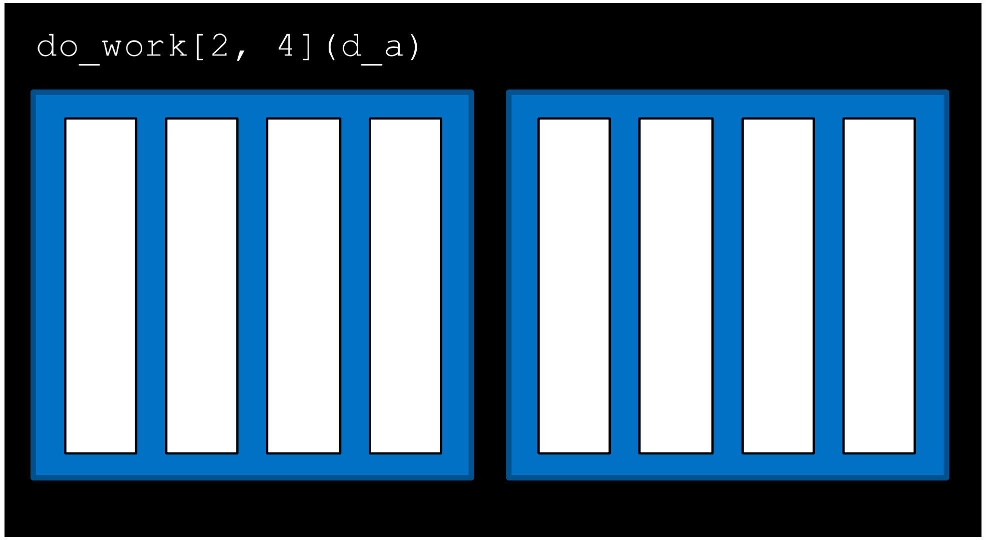
CUDA Thread Hierarchy

Let’s dig into what happens when we launch a function on the GPU



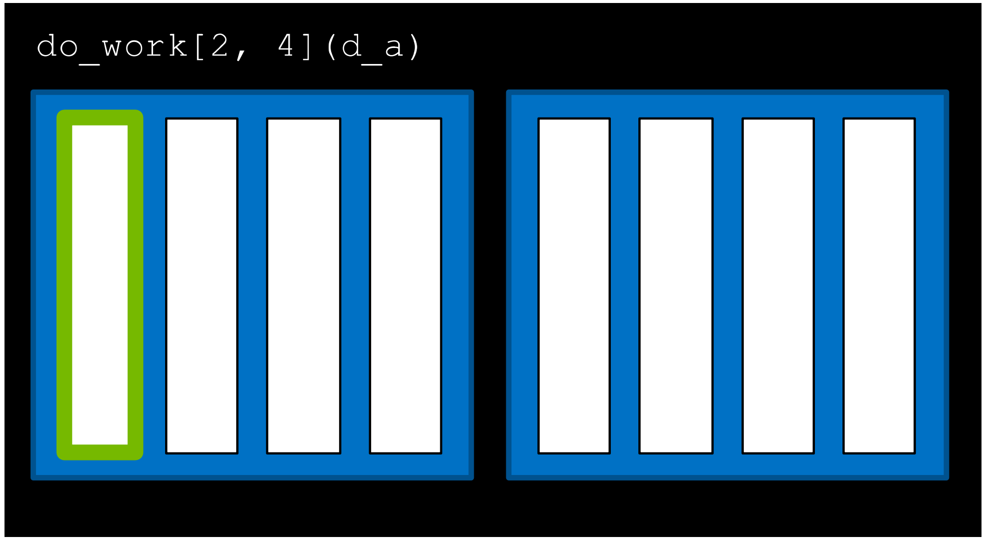
GPUs do work in parallel

GPU



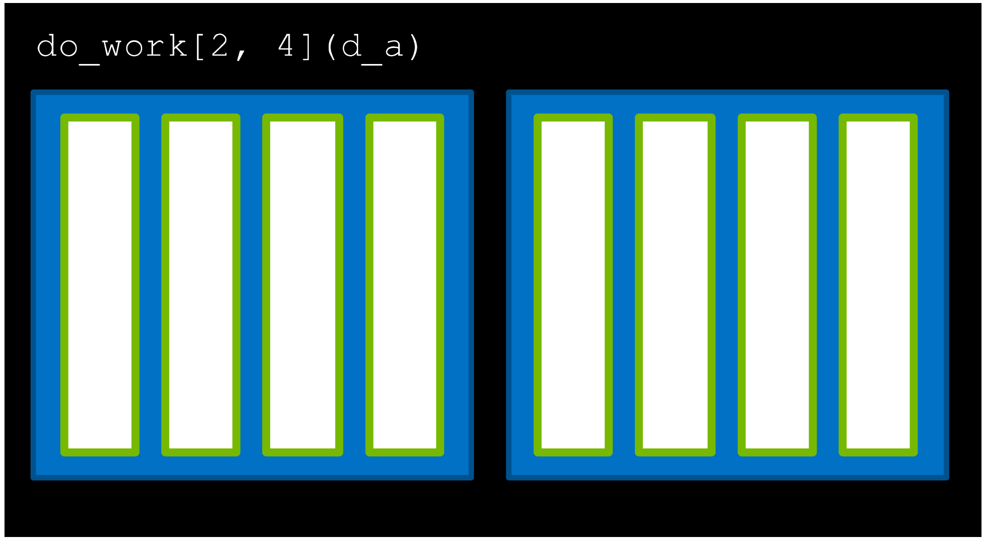
GPU work is done in a **thread**

GPU



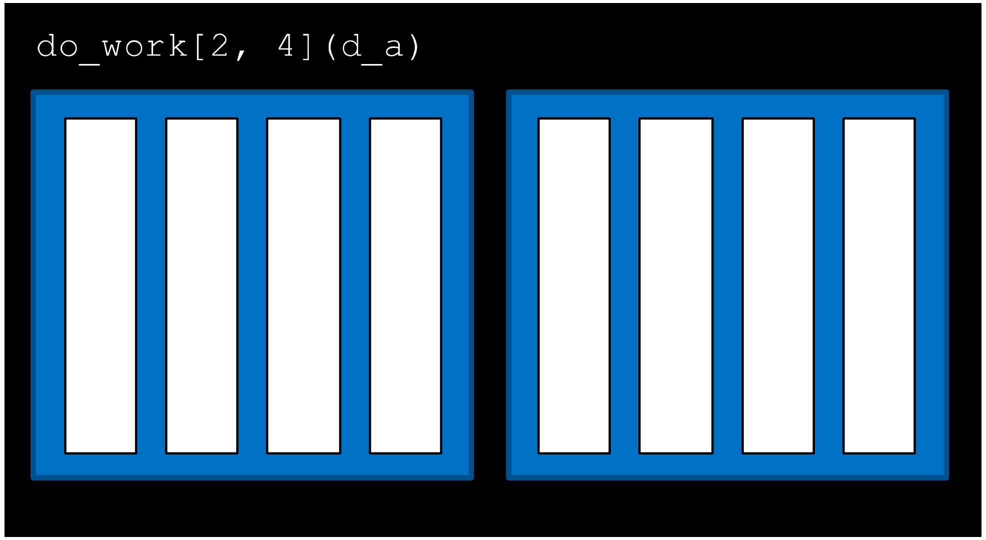
Many threads run in parallel

GPU



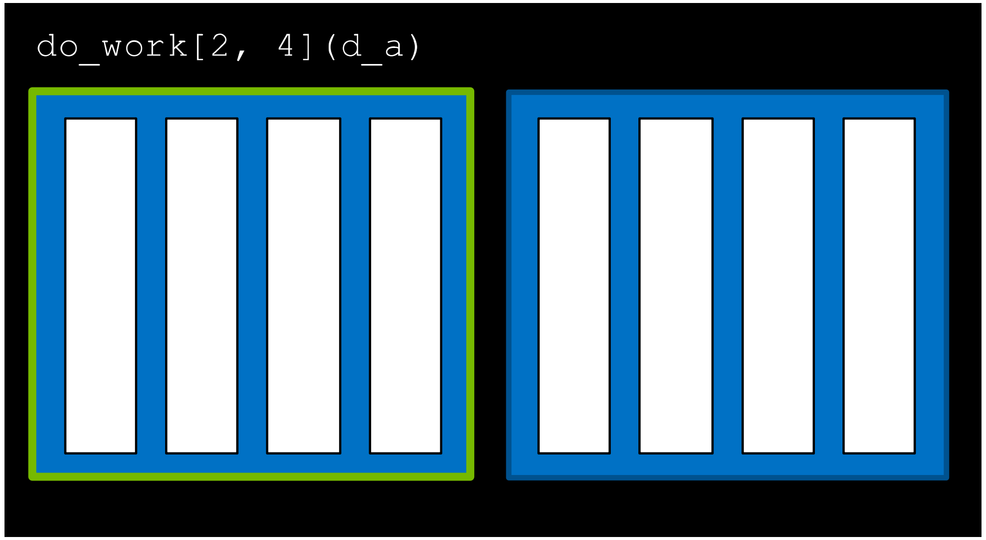
CUDA can process thousands of threads in parallel. The sizes are greatly reduced in these images for simplicity.

GPU



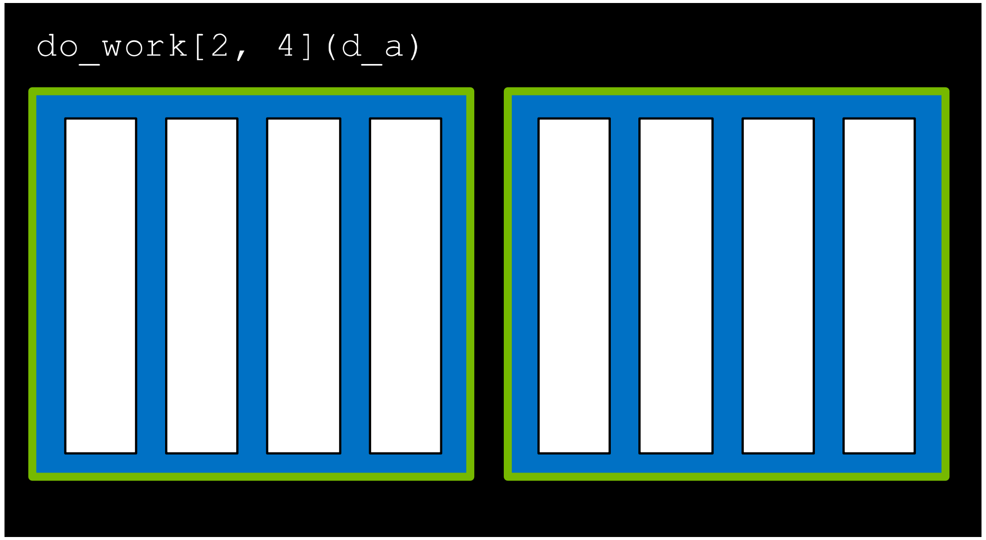
A collection of threads is a **block**

GPU



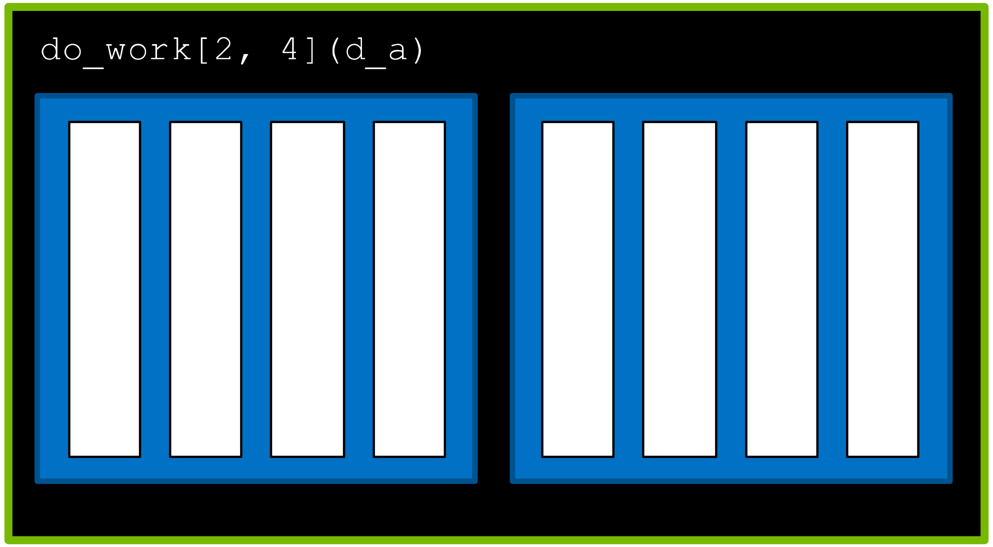
There can be many blocks

GPU



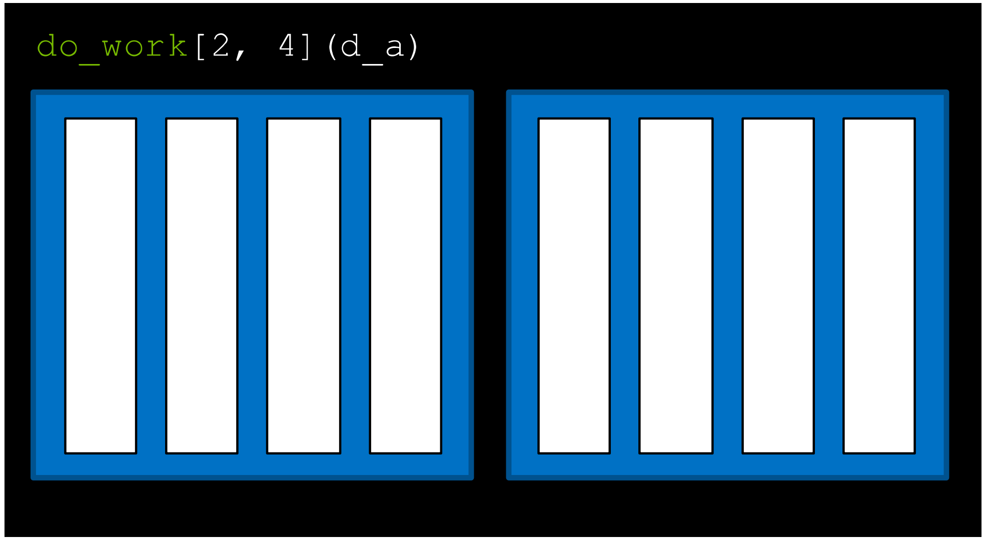
A collection of blocks associated with a given kernel launch is a **grid**

GPU



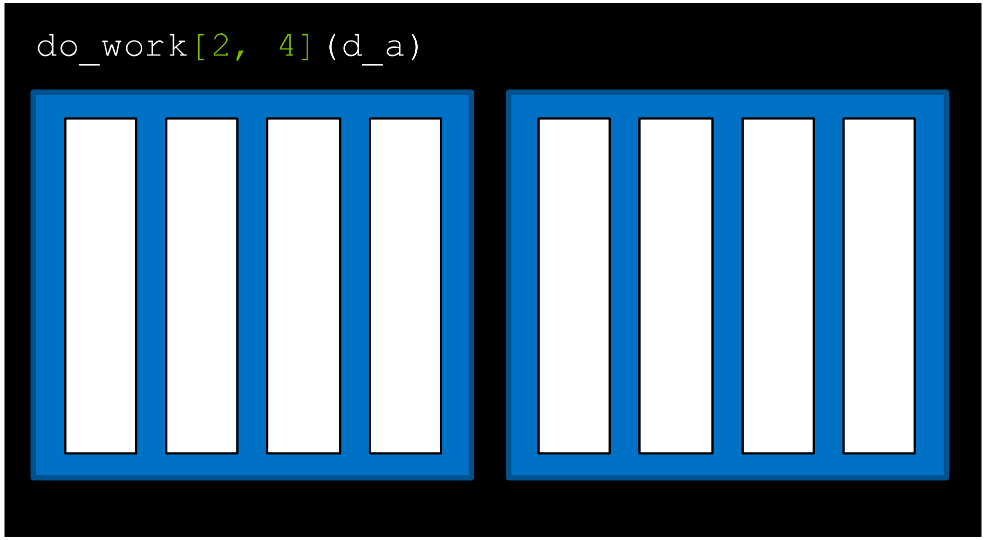
GPU functions are called **kernels**

GPU



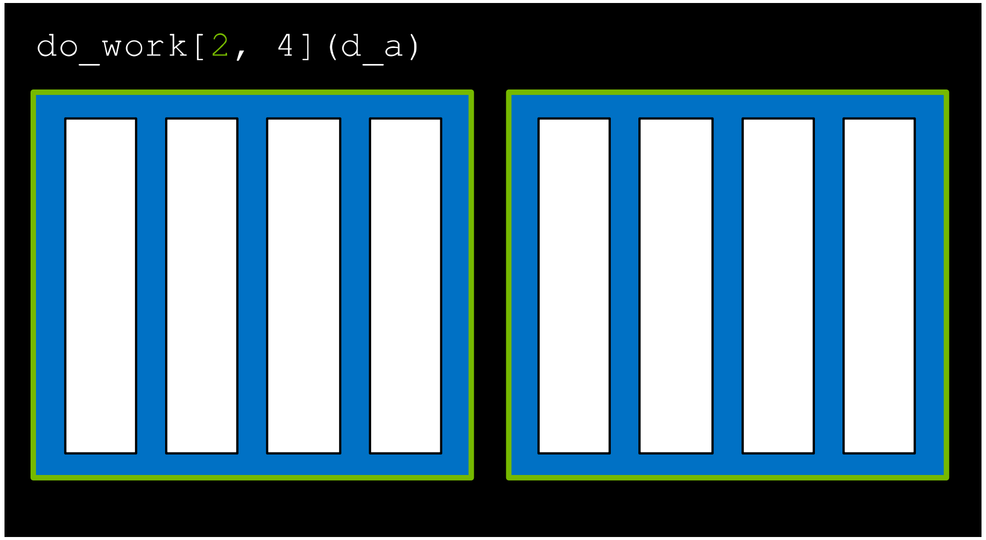
Kernels are **launched** with an **execution configuration**

GPU



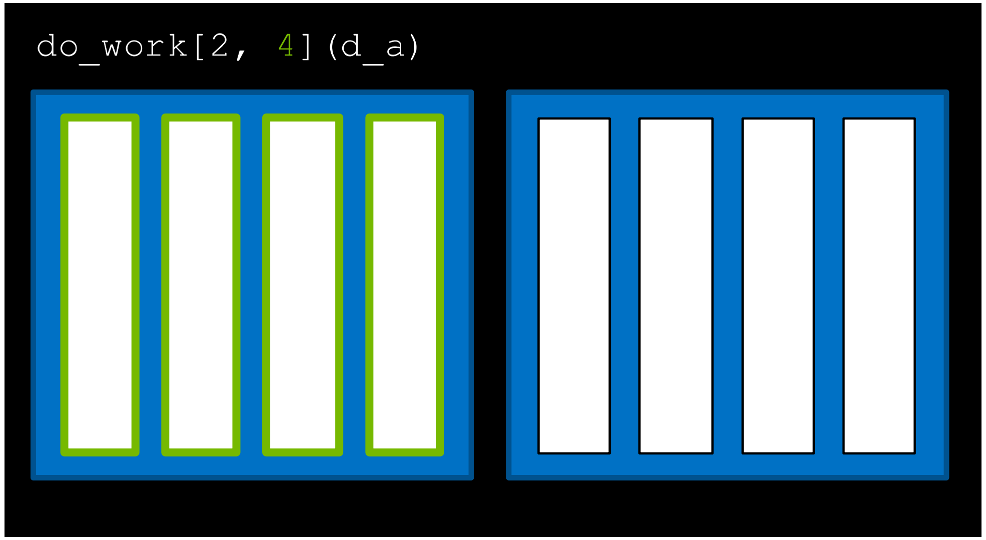
The execution configuration defines the number of blocks in the grid

GPU



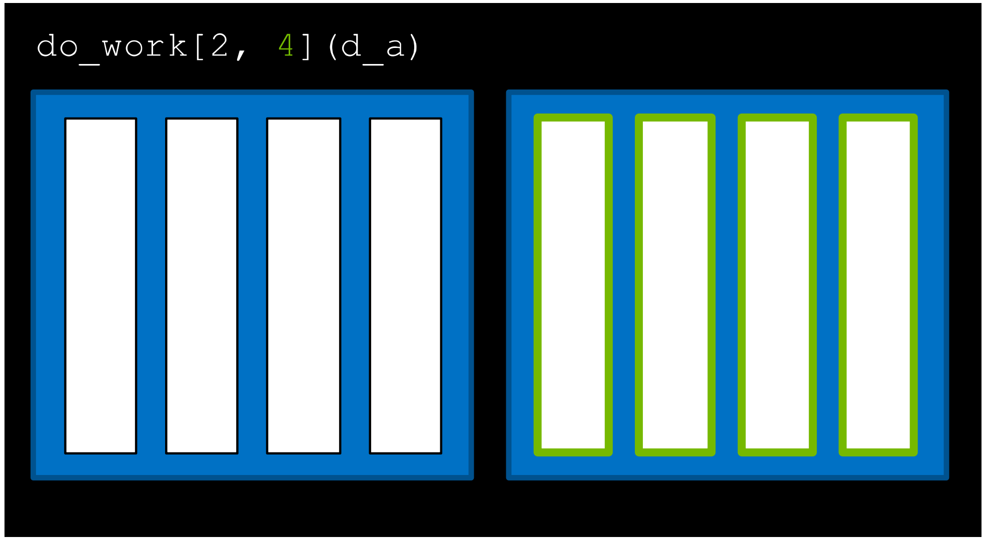
… as well as the number of threads in each block

GPU



Every block in the grid contains the same number of threads

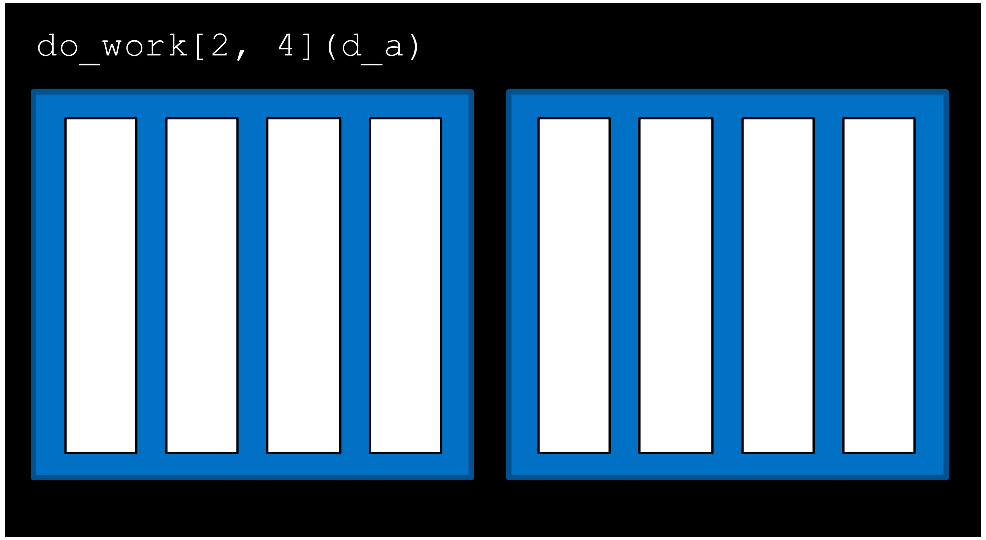
GPU



CUDA-Provided Thread Hierarchy Variables

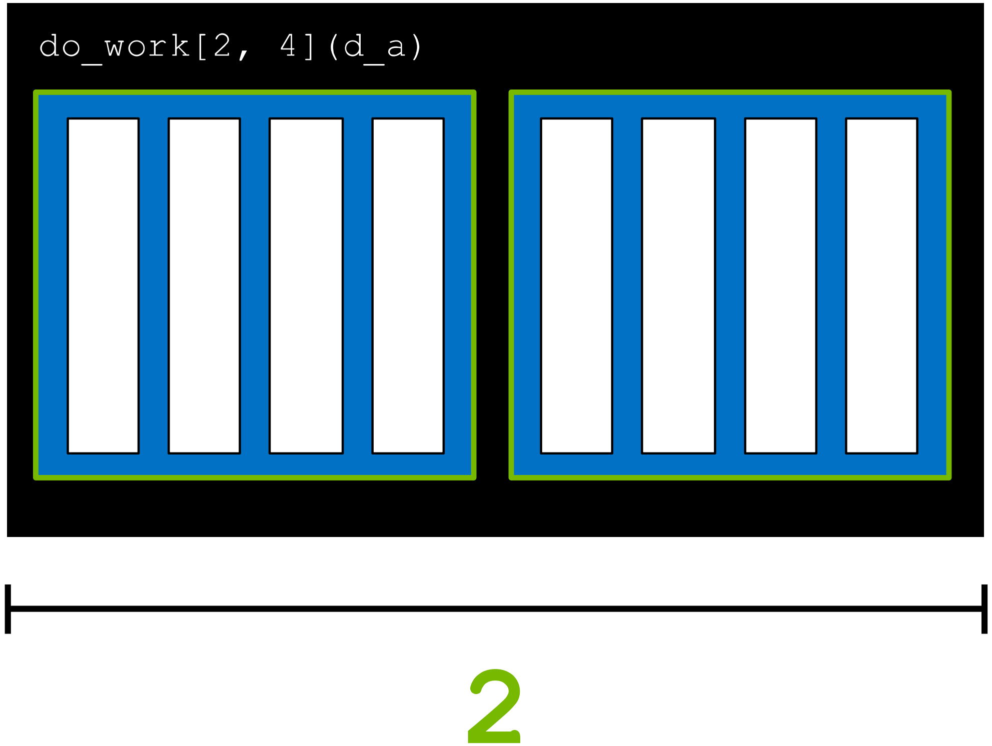
Inside kernel definitions, CUDA-provided variables describe its executing thread, block, and grid

GPU



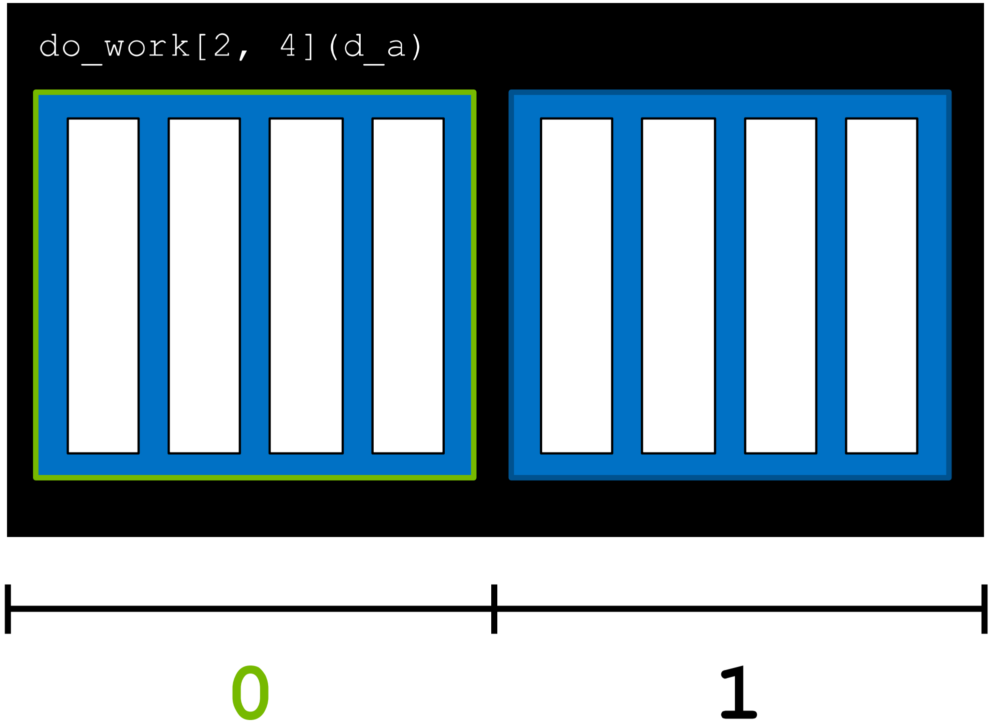
`gridDim.x` is the number of blocks in the grid, in this case **2**

GPU



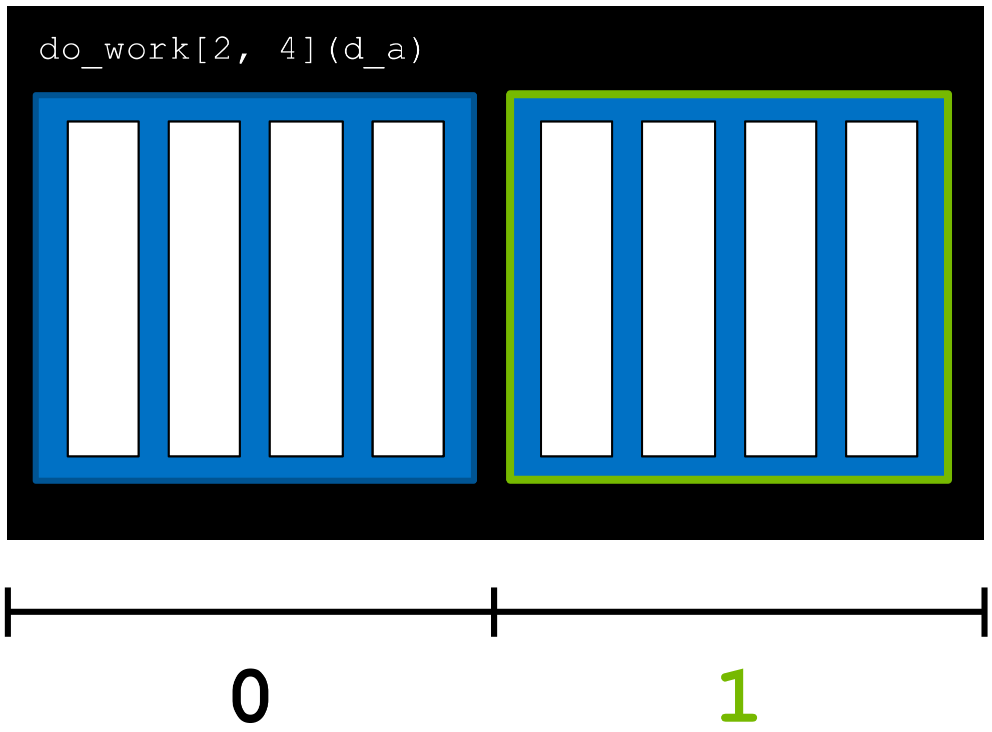
`blockIdx.x` is the index of the current block within the grid, in this case **0**

GPU



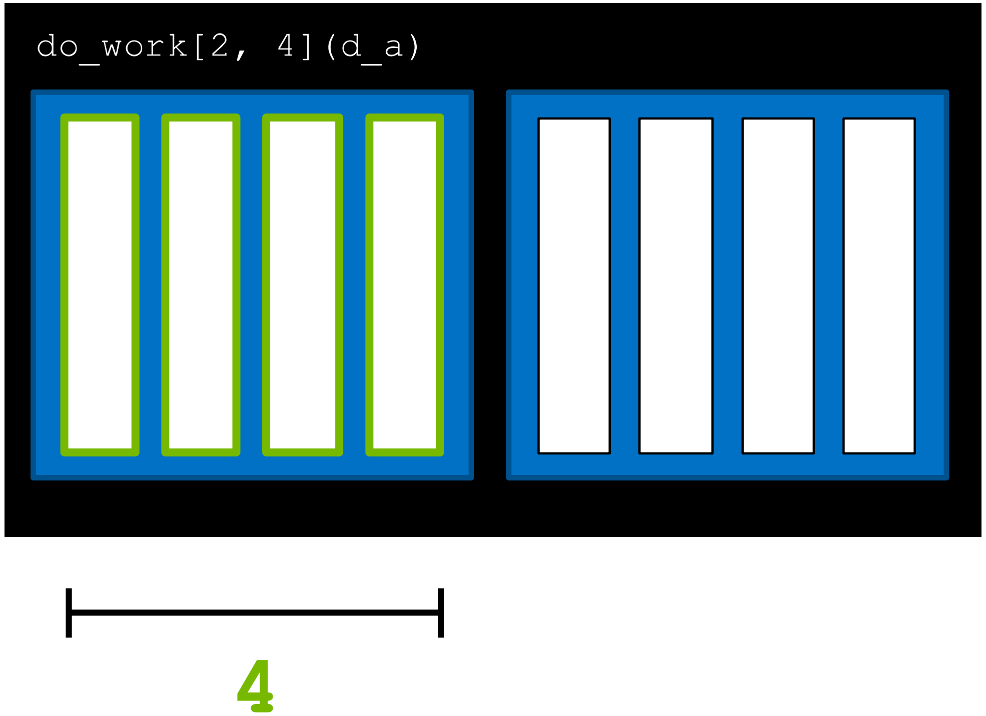
`blockIdx.x` is the index of the current block within the grid, in this case **`1`**

GPU



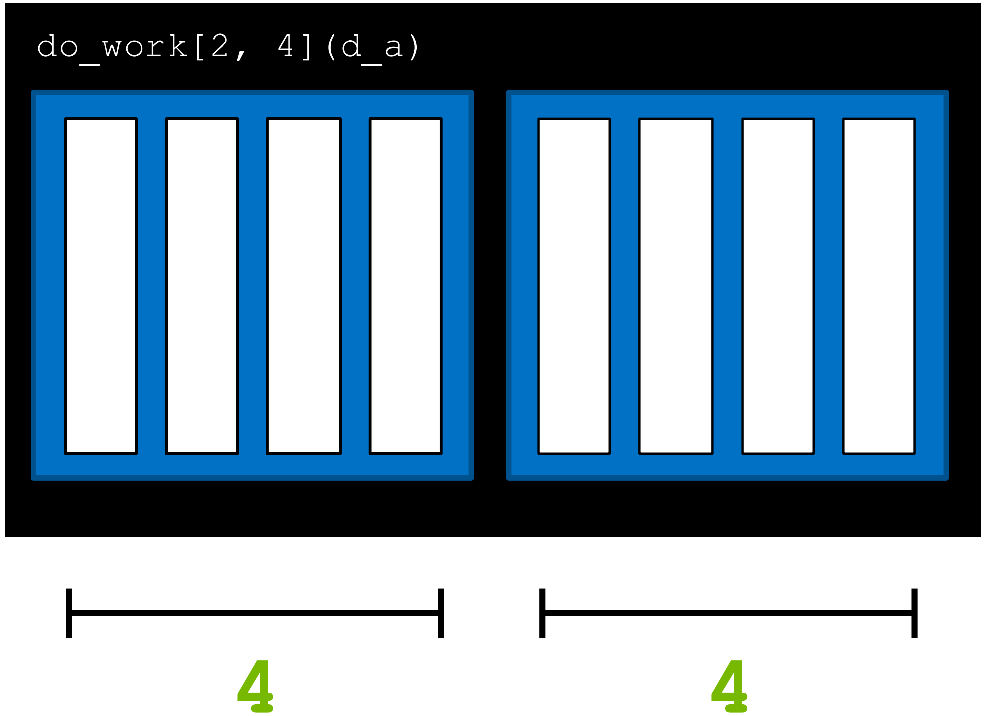
Inside a kernel **`blockDim.x`** describes the number of threads in a block. In this case **`4`**

GPU



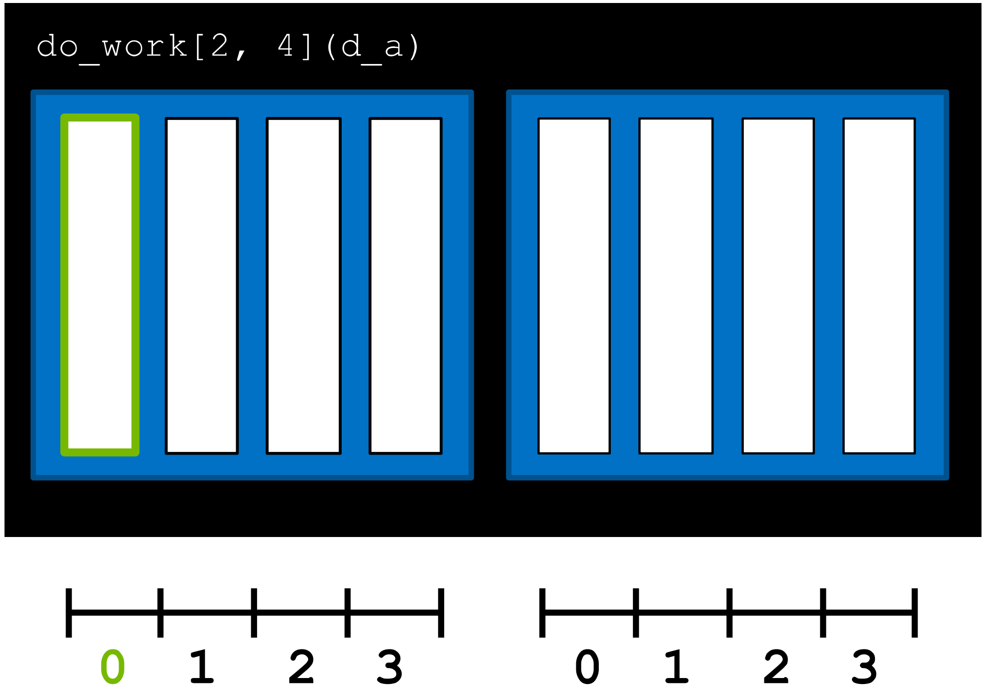
All blocks in a grid contain the same number of threads

GPU



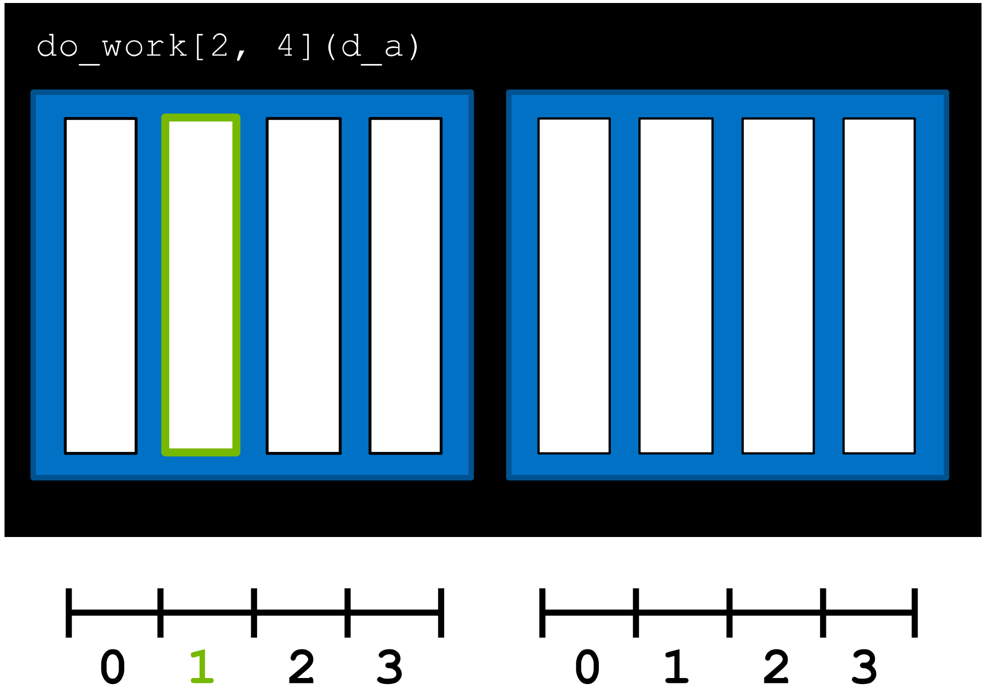
Inside a kernel **`threadIdx.x`** describes the index of the thread within a block. In this case **`0`**

GPU



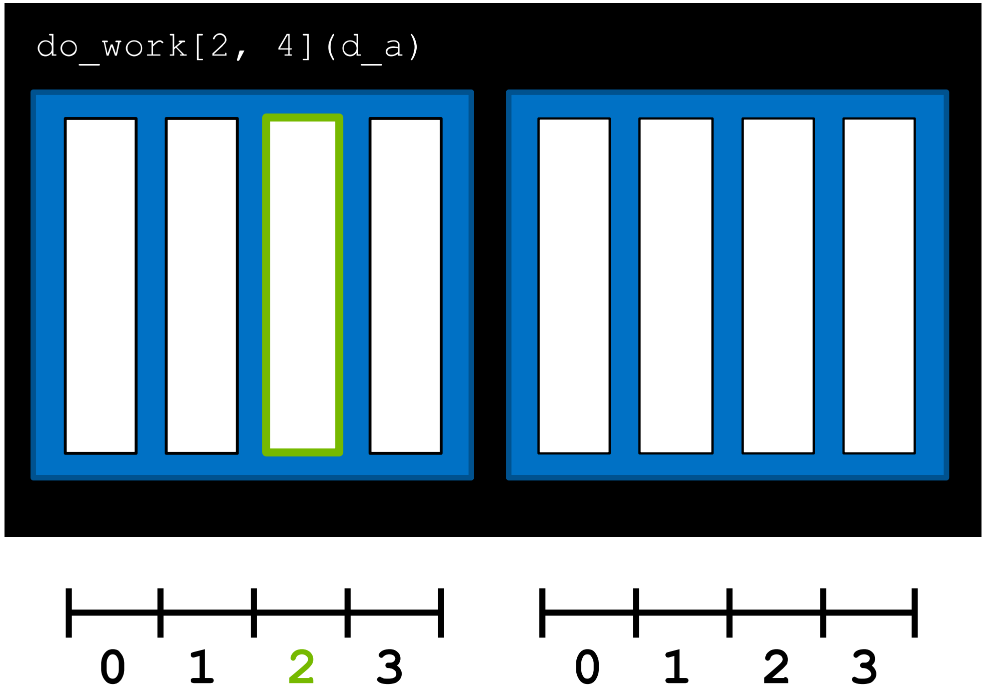
Inside a kernel **`threadIdx.x`** describes the index of the thread within a block. In this case **`1`**

GPU



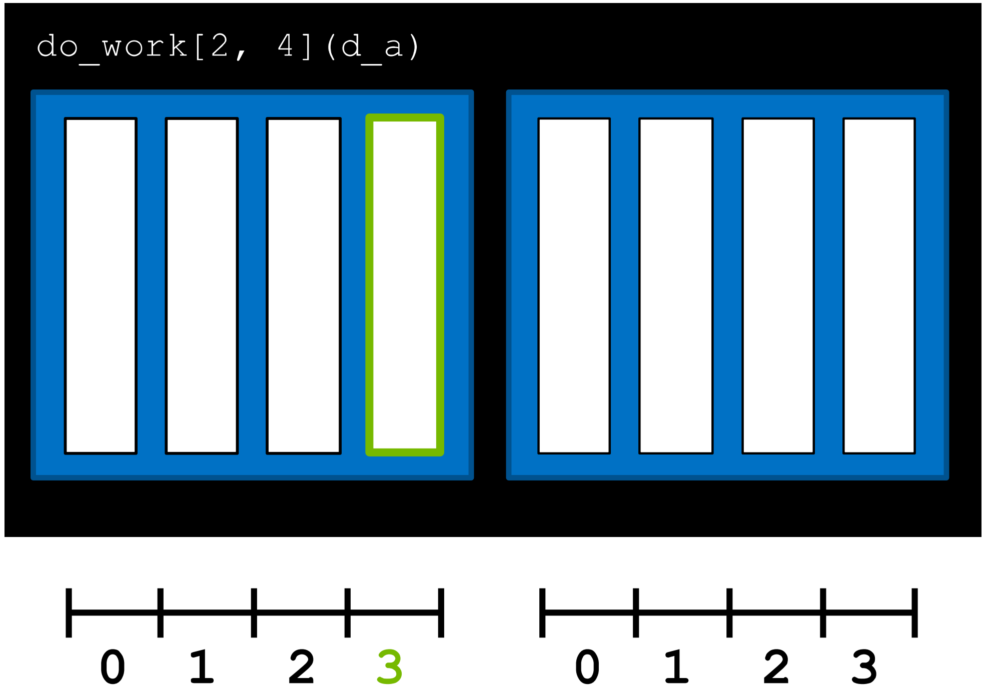
Inside a kernel **`threadIdx.x`** describes the index of the thread within a block. In this case **2**

GPU



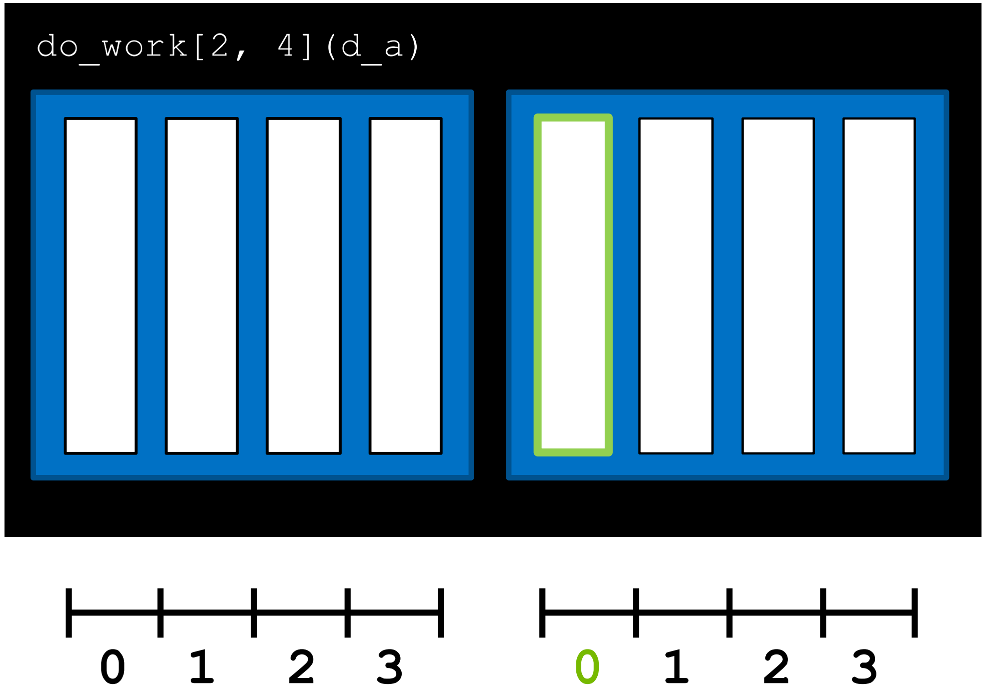
Inside a kernel **`threadIdx.x`** describes the index of the thread within a block. In this case **3**

GPU



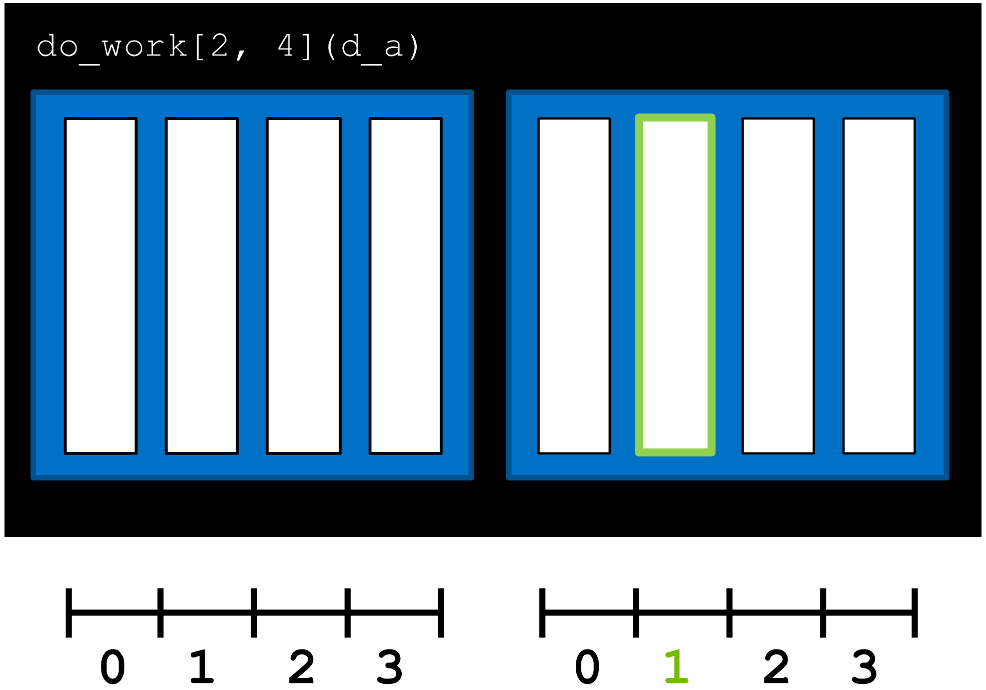
Inside a kernel **`threadIdx.x`** describes the index of the thread within a block. In this case **0**

GPU



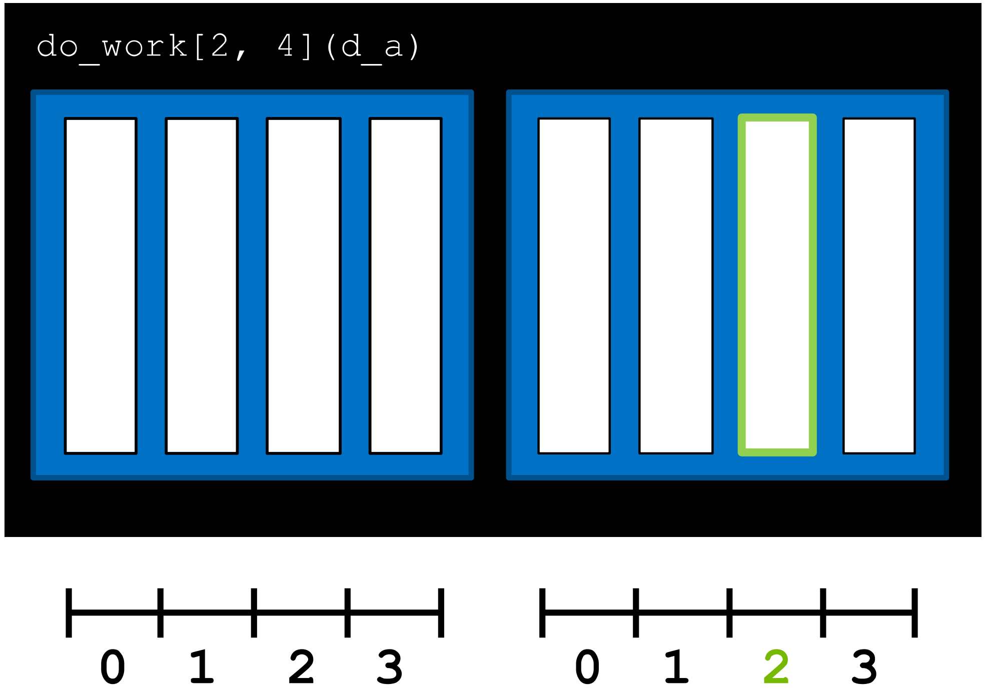
Inside a kernel `threadIdx.x` describes the index of the thread within a block. In this case `1`

GPU



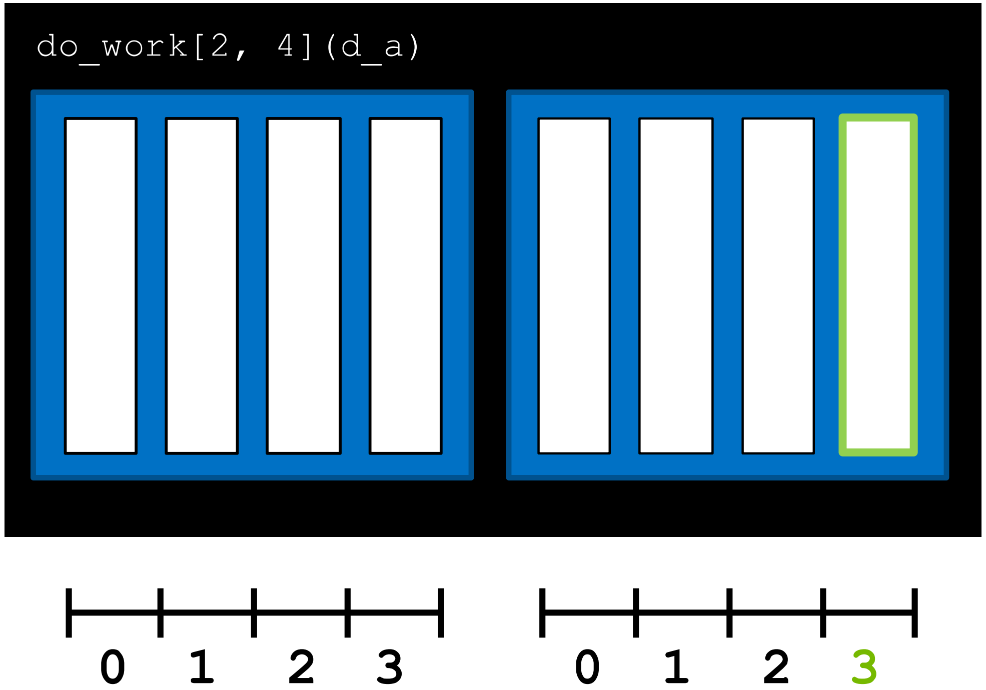
Inside a kernel **`threadIdx.x`** describes the index of the thread within a block. In this case **2**

GPU



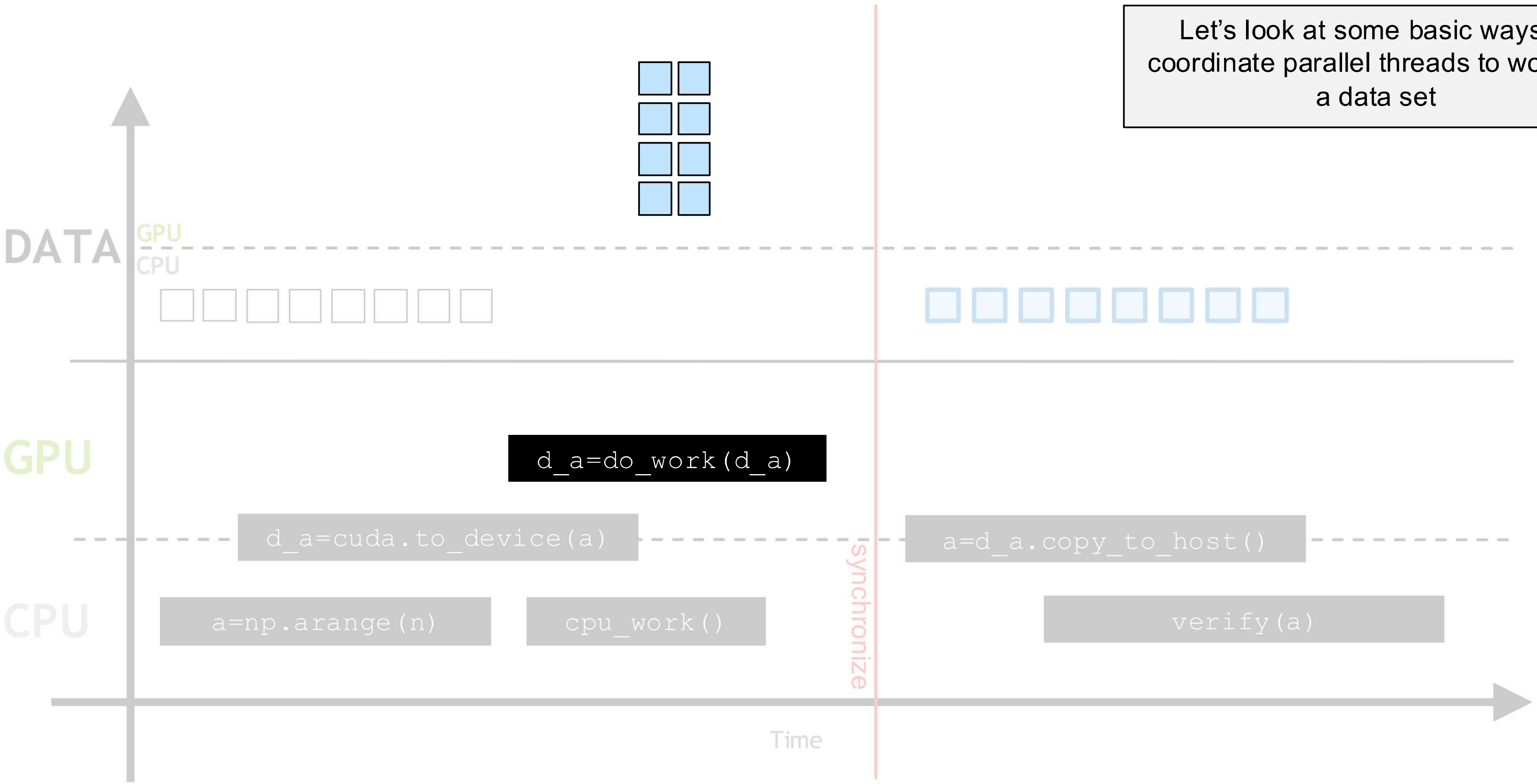
Inside a kernel **`threadIdx.x`** describes the index of the thread within a block. In this case **`3`**

GPU

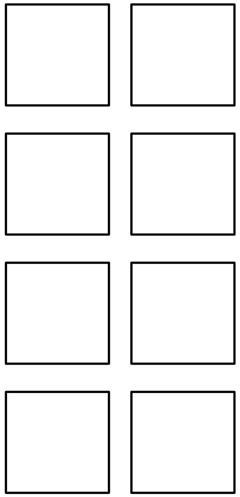


Coordinating Parallel Threads

Let’s look at some basic ways to coordinate parallel threads to work on a data set

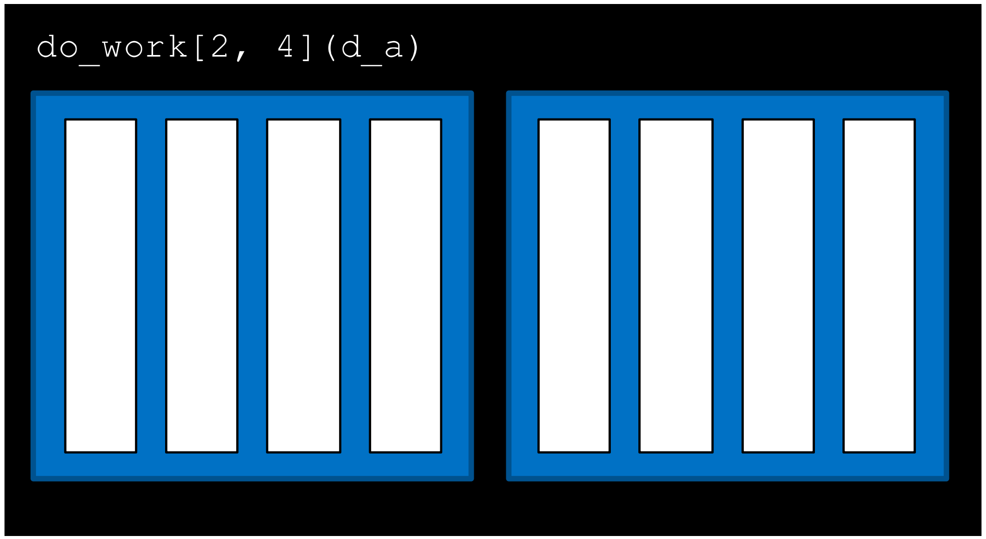


GPU
DATA

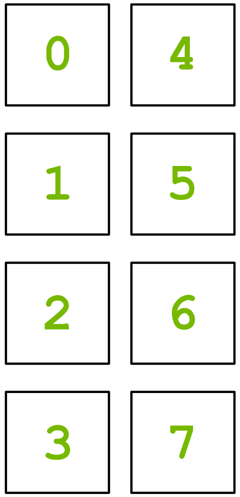


Assume data is in a 0 indexed vector

GPU

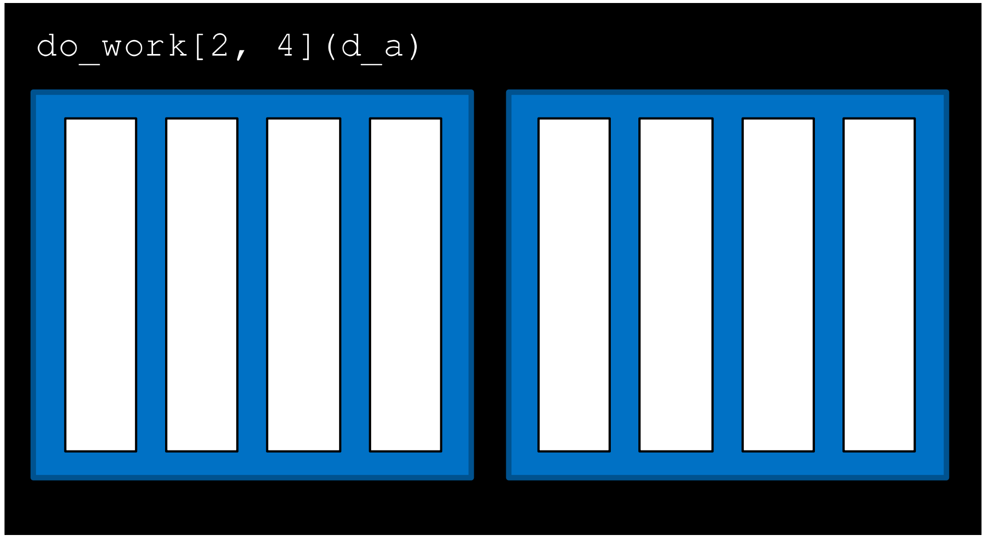


GPU
DATA

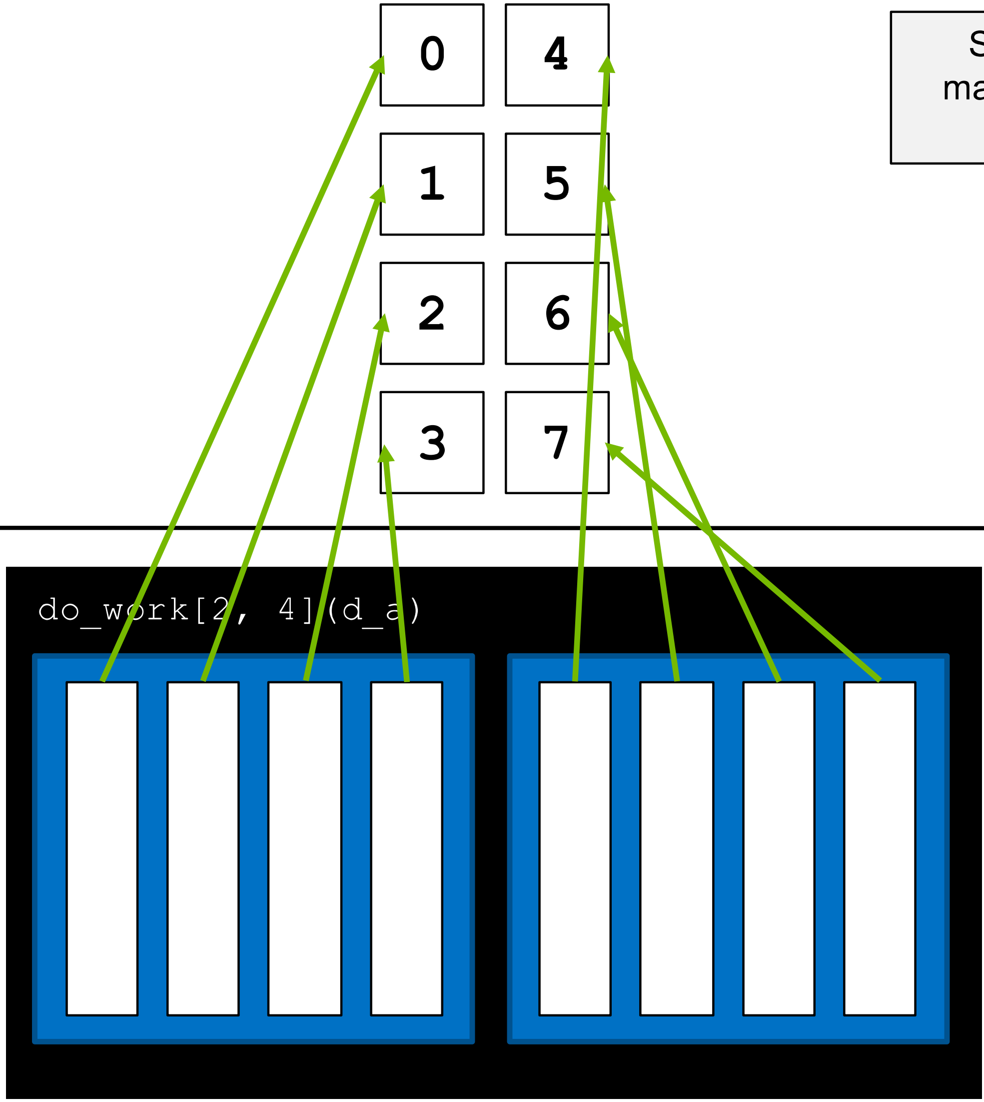


Assume data is in a 0 indexed vector

GPU

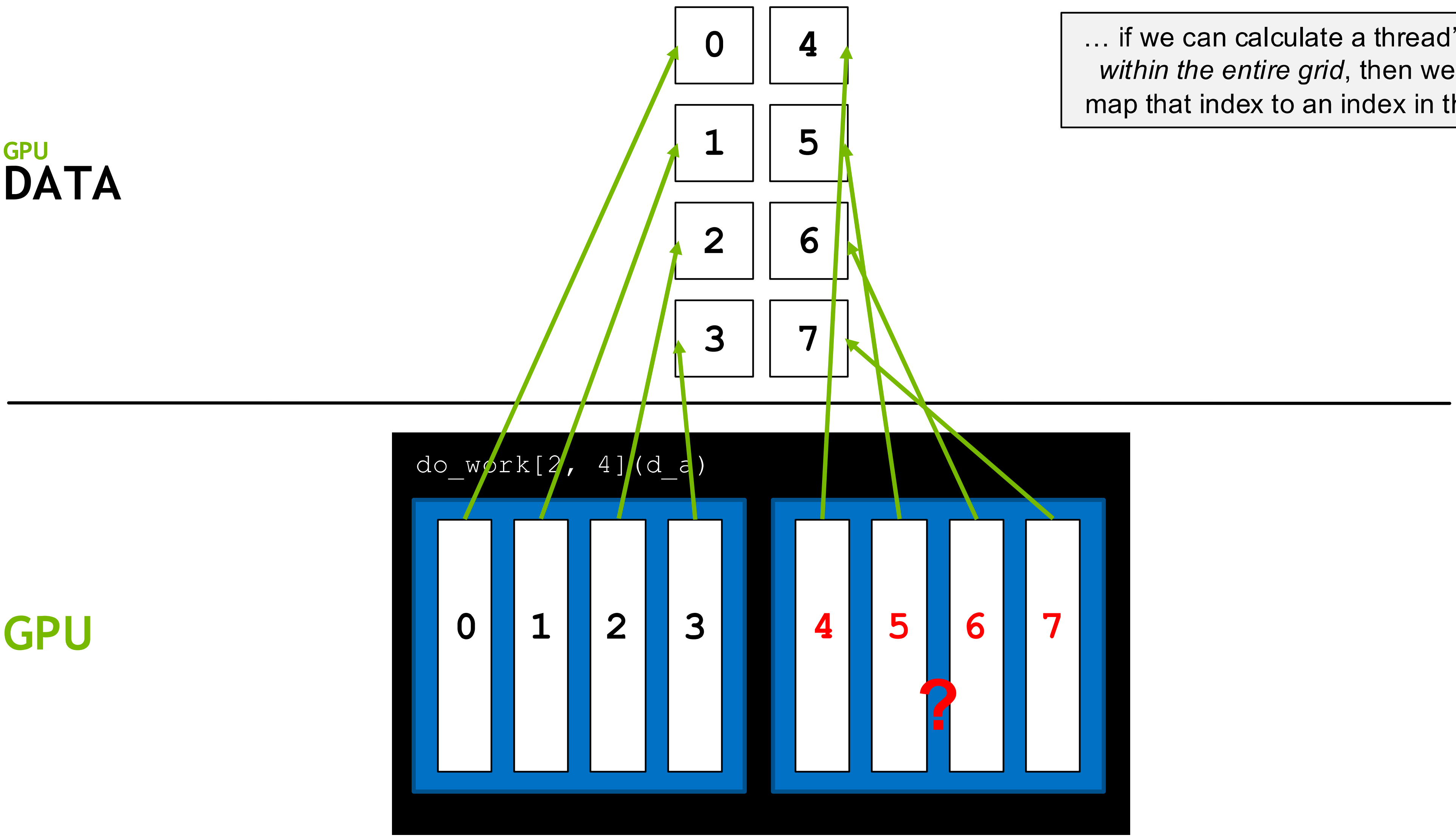


GPU
DATA

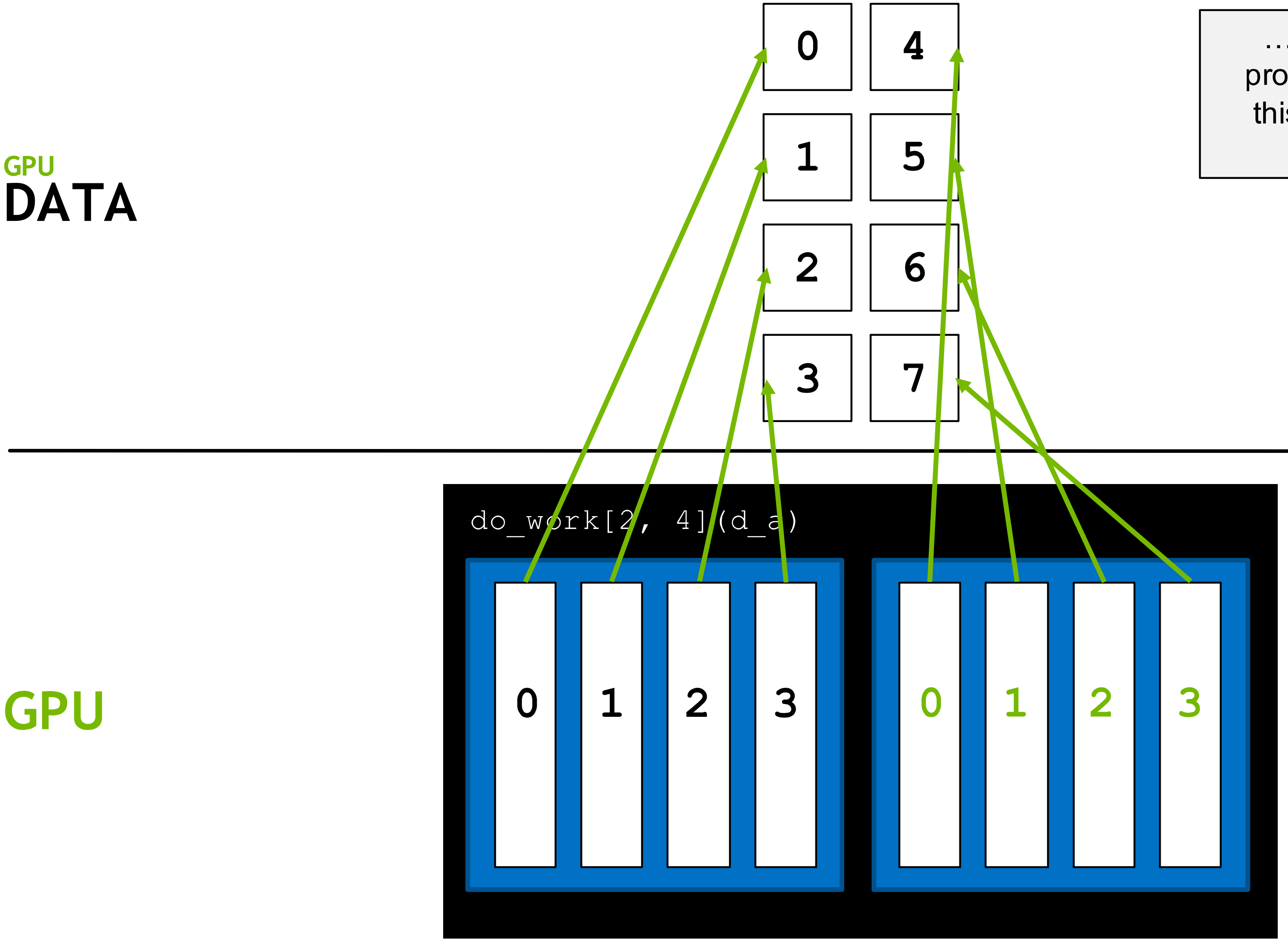


Somehow, each thread must be mapped to work on elements in the data

GPU

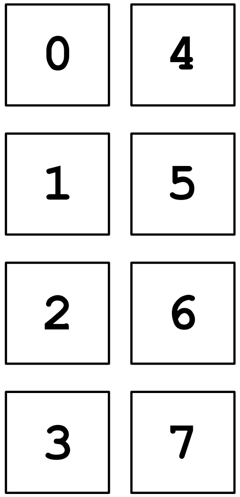


… if we can calculate a thread's index *within the entire grid*, then we could map that index to an index in the data



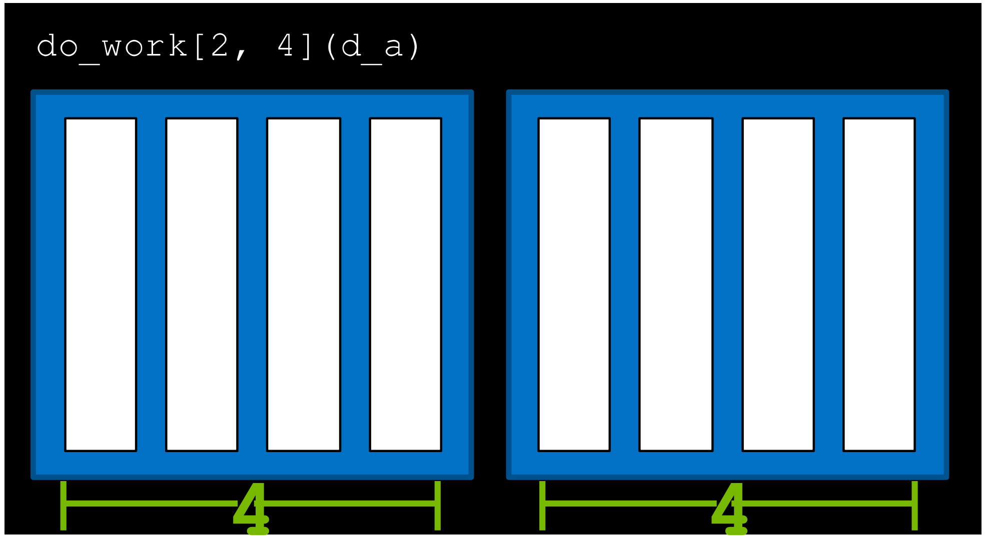
… unfortunately CUDA does not provide a single variable to capture this, only thread indices *within the block*

GPU
DATA

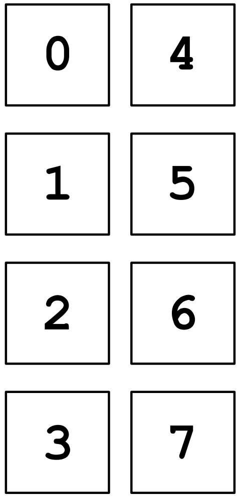


There is an idiomatic way to calculate this value, however. Recall that each thread has access to the size of its block via **`blockDim.x`**

GPU

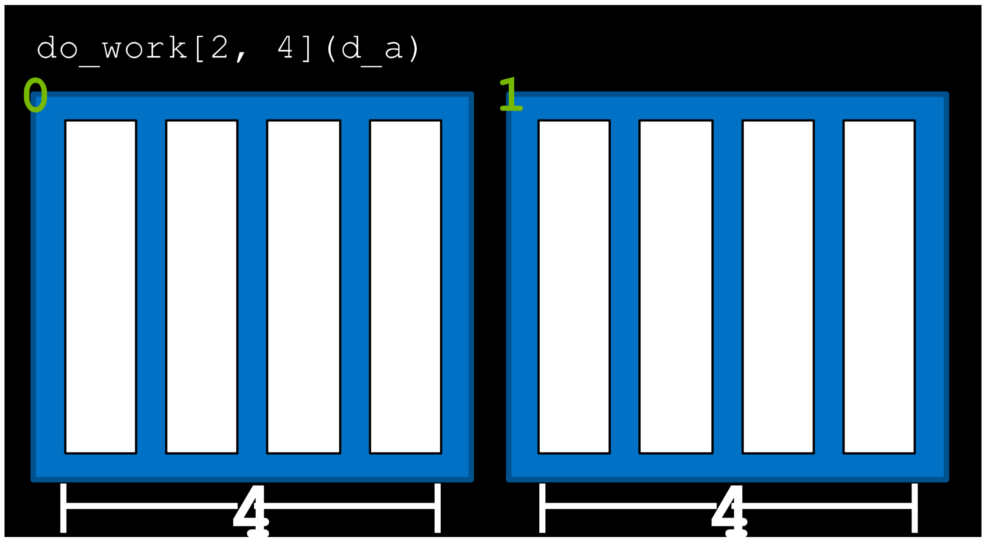


GPU
DATA

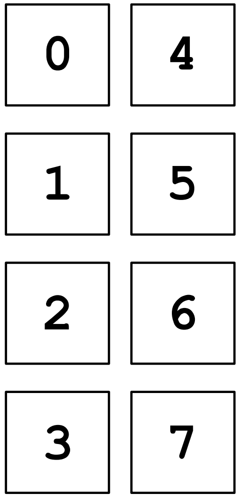


…and the index of its block within the grid via **`blockIdx.x`**

GPU

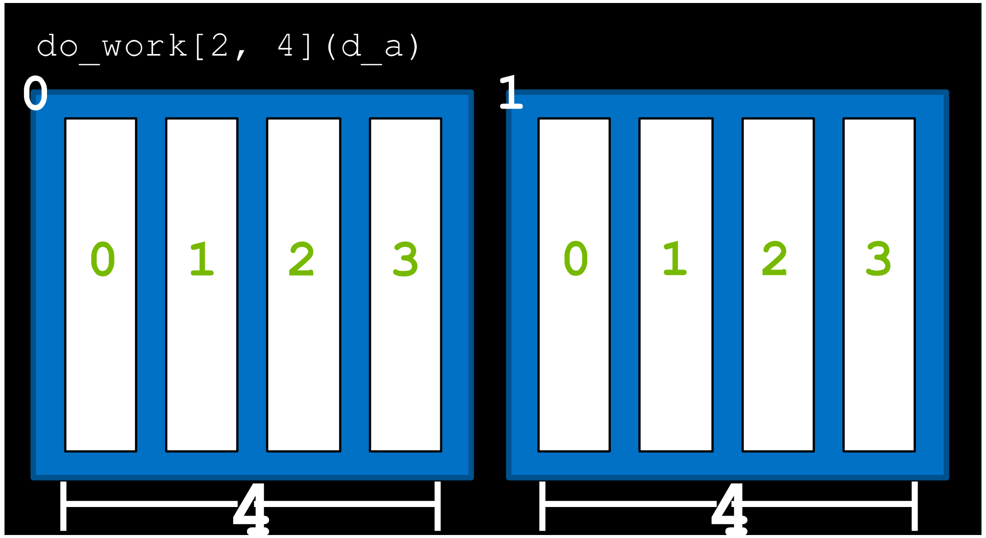


GPU
DATA



…and its own index within its block via **`threadIdx.x`**

GPU



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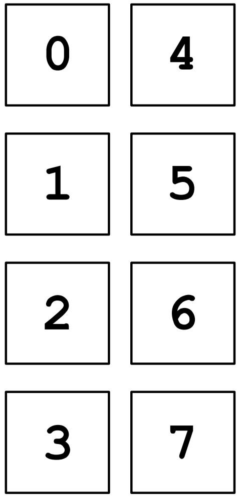
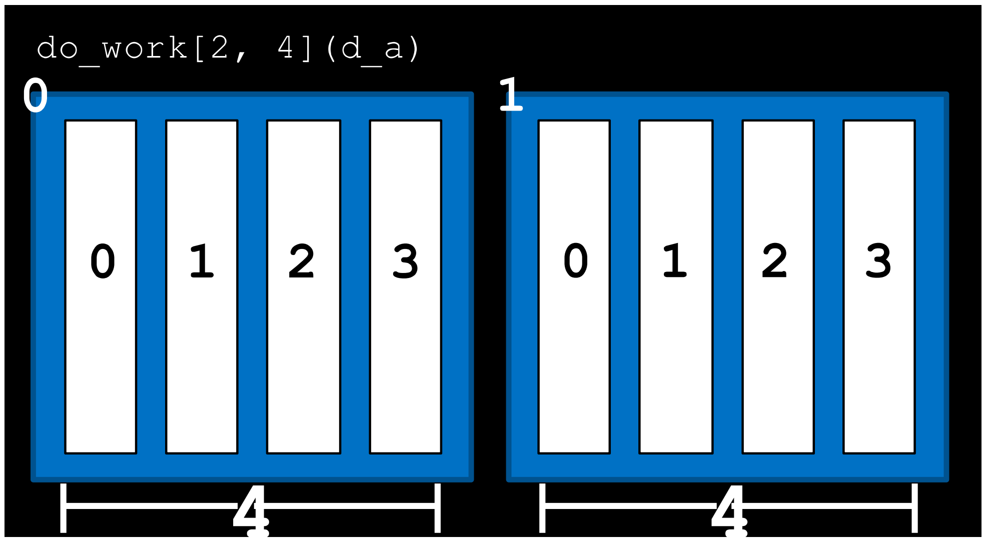
GPU

DATA



Using these variables, the formula **`threadIdx.x + blockIdx.x * blockDim.x`** will return the thread's unique index in the whole grid, which we can then map to data elements.

GPU



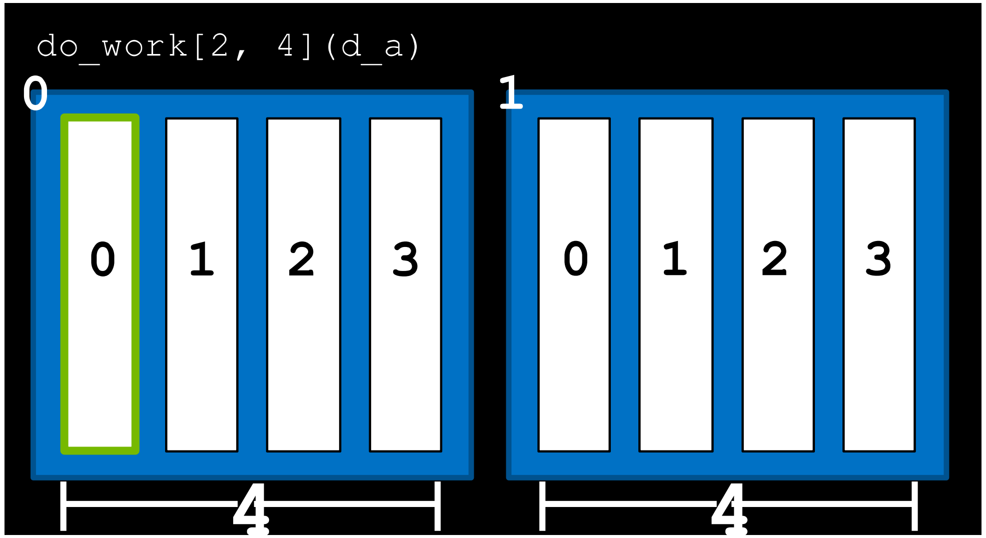
GPU
DATA

0	4
1	5
2	6
3	7

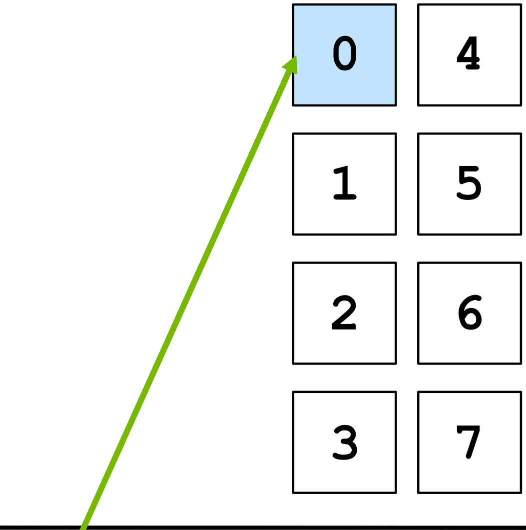
threadIdx.x	+	blockIdx.x	*	blockDim.x
0		0		4

data_index
?

GPU



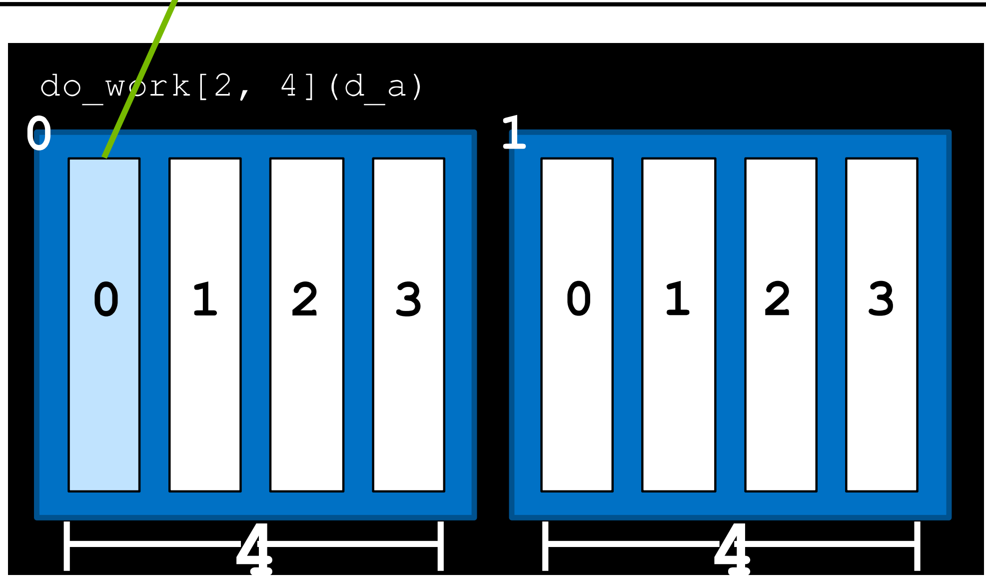
GPU
DATA



threadIdx.x	+	blockIdx.x	*	blockDim.x
0		0		4

data_index
0

GPU



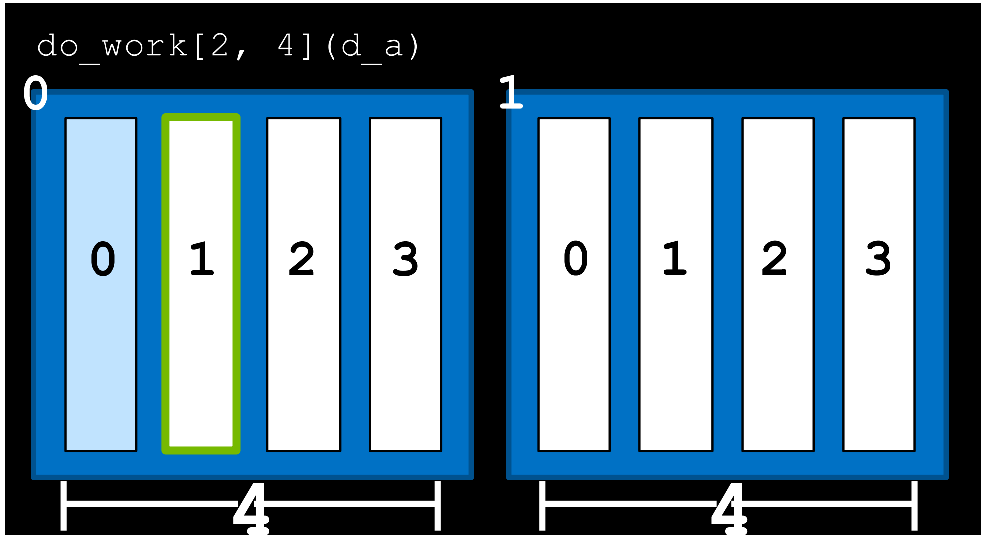
GPU
DATA

0	4
1	5
2	6
3	7

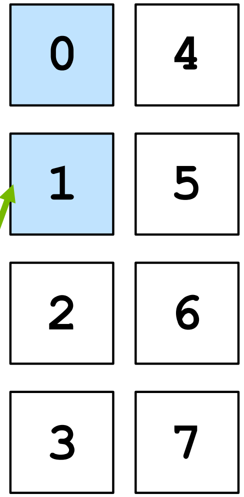
threadIdx.x	+	blockIdx.x	*	blockDim.x
1		0		4

data_index
?

GPU



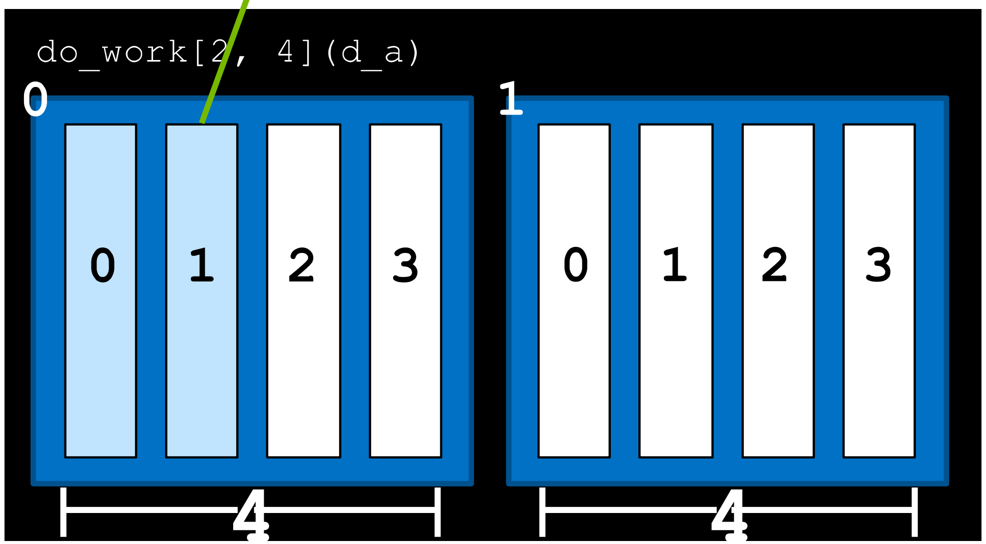
GPU
DATA



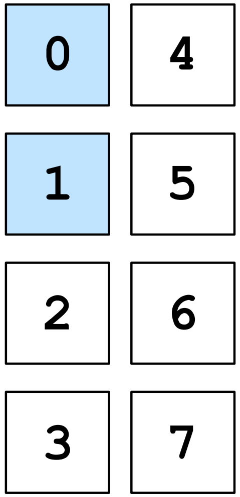
threadIdx.x	+	blockIdx.x	*	blockDim.x
1		0		4

data_index
1

GPU



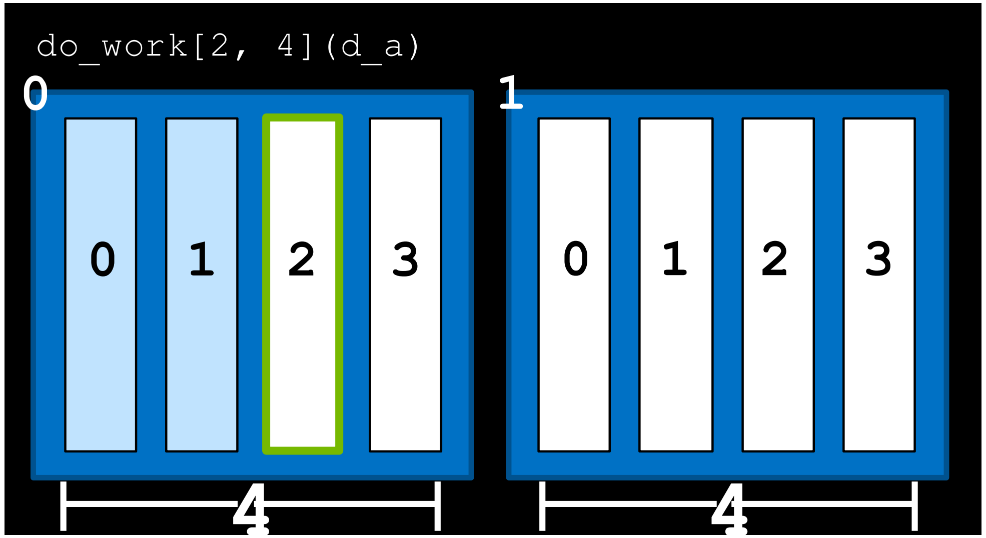
GPU
DATA



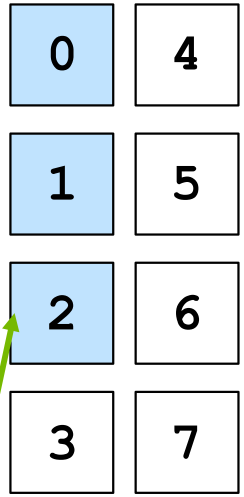
threadIdx.x	+	blockIdx.x	*	blockDim.x
2		0		4

data_index
?

GPU



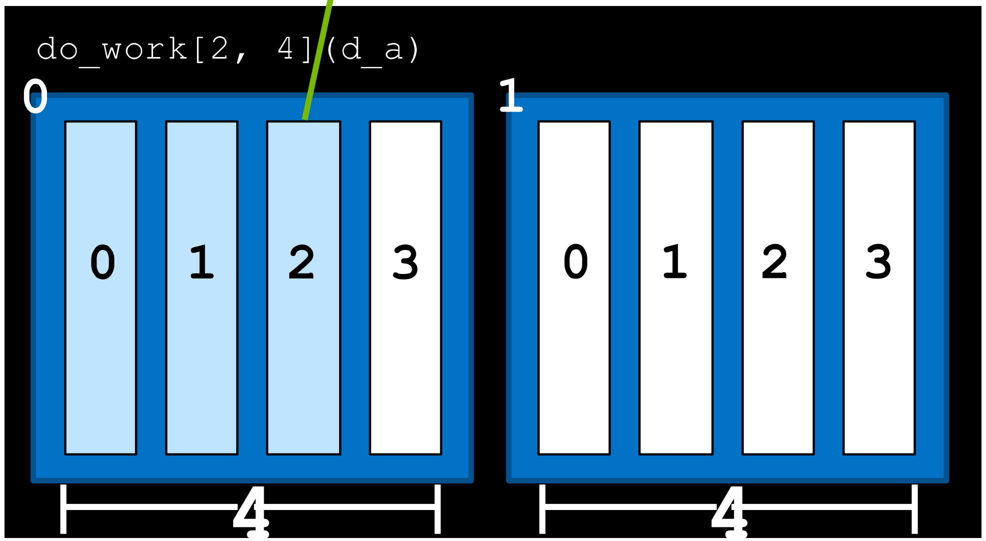
GPU
DATA



threadIdx.x	+	blockIdx.x	*	blockDim.x
2		0		4

data_index
2

GPU



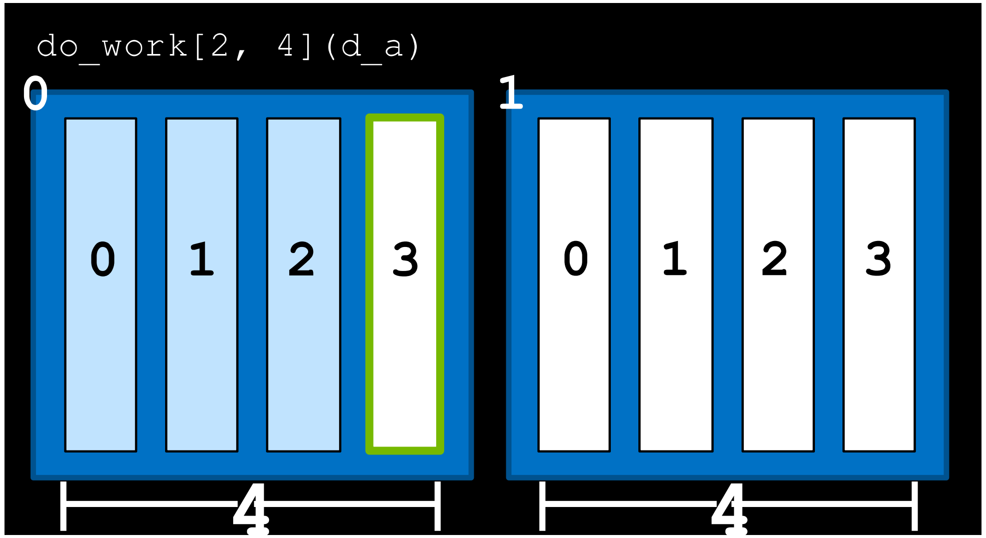
GPU
DATA

0	4
1	5
2	6
3	7

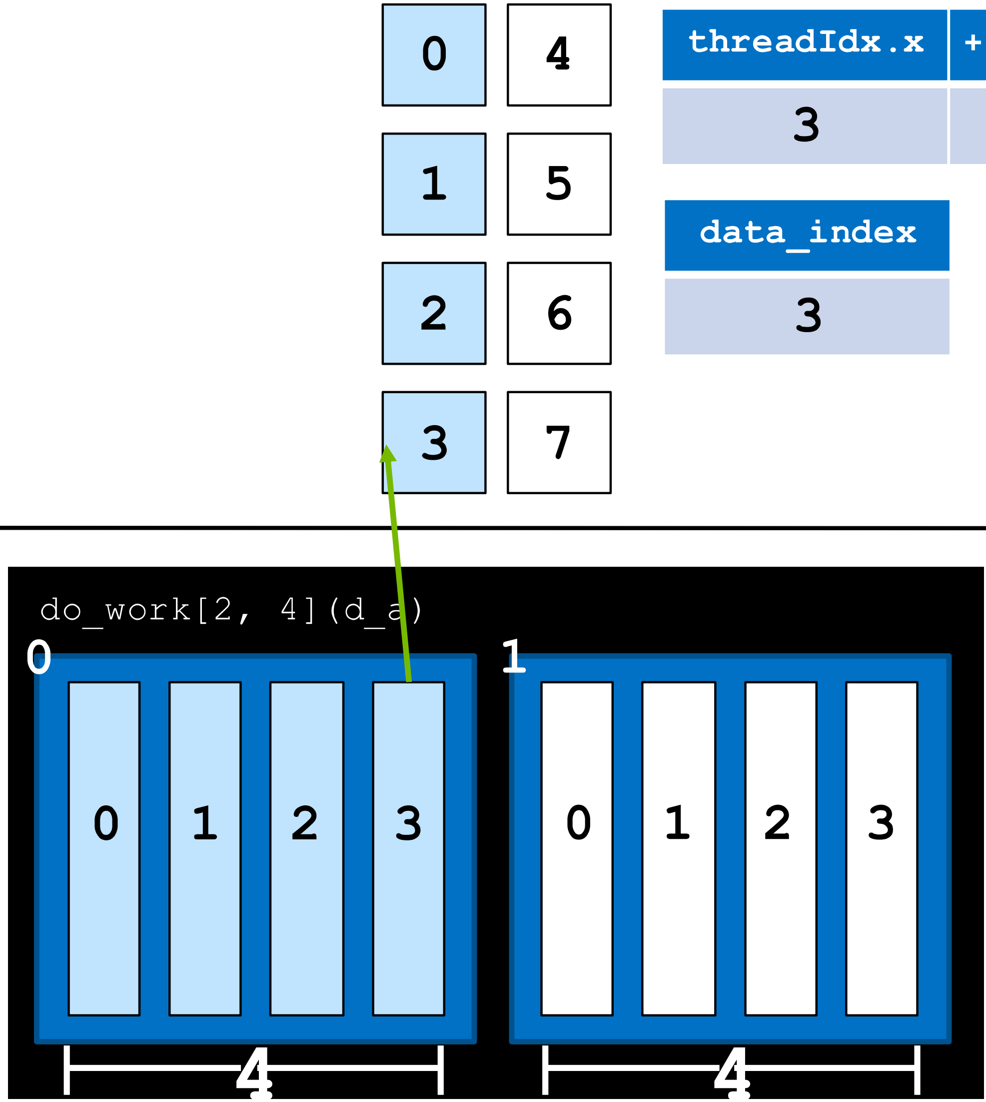
threadIdx.x	+	blockIdx.x	*	blockDim.x
3		0		4

data_index
?

GPU



GPU
DATA

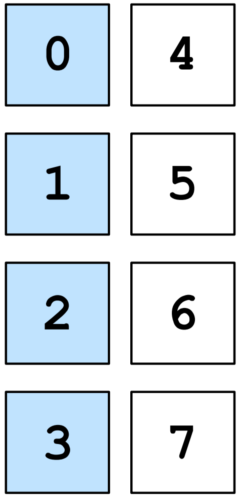


threadIdx.x	+	blockIdx.x	*	blockDim.x
3		0		4

data_index
3

GPU

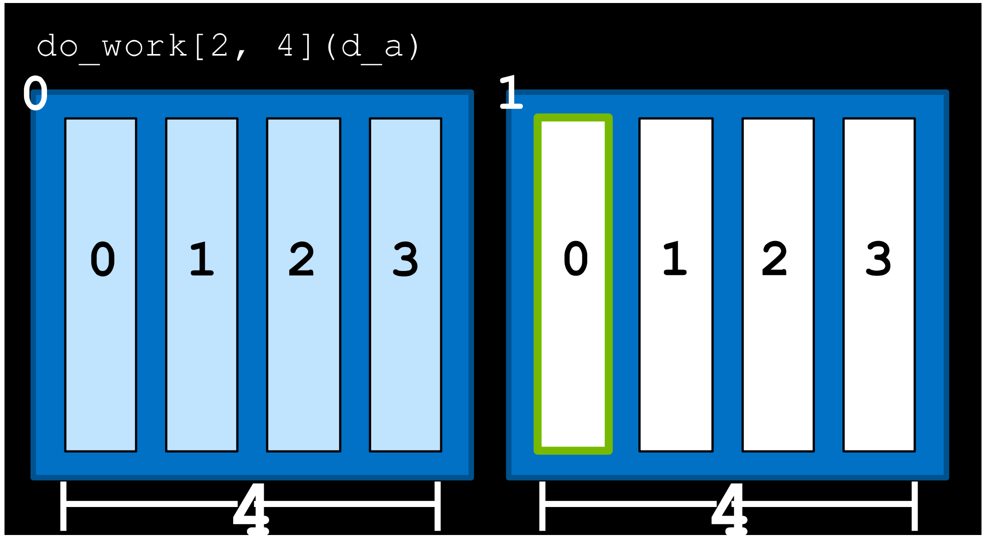
GPU
DATA



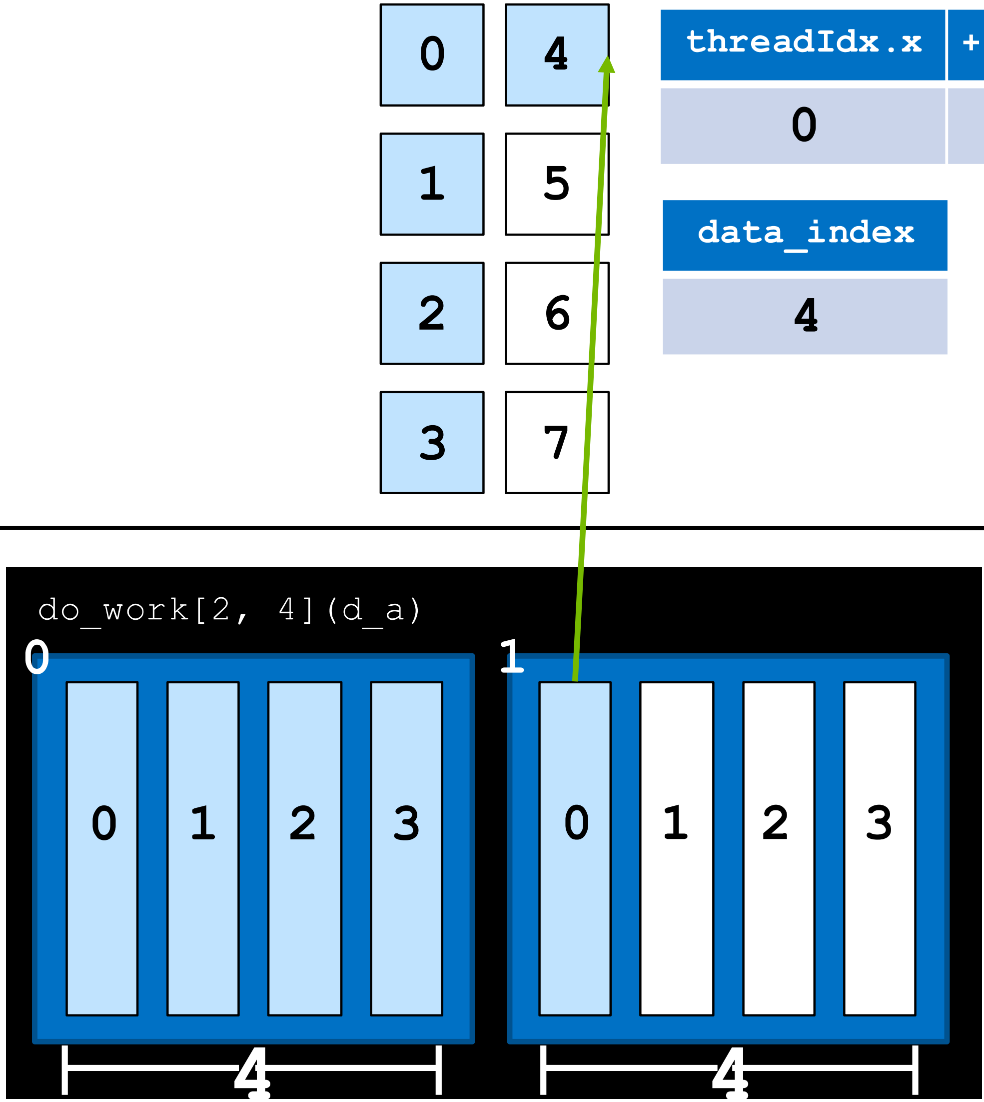
threadIdx.x	+	blockIdx.x	*	blockDim.x
0		1		4

data_index
?

GPU



GPU
DATA

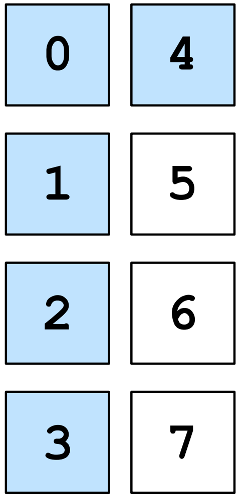


threadIdx.x	+	blockIdx.x	*	blockDim.x
0		1		4

data_index
4

GPU

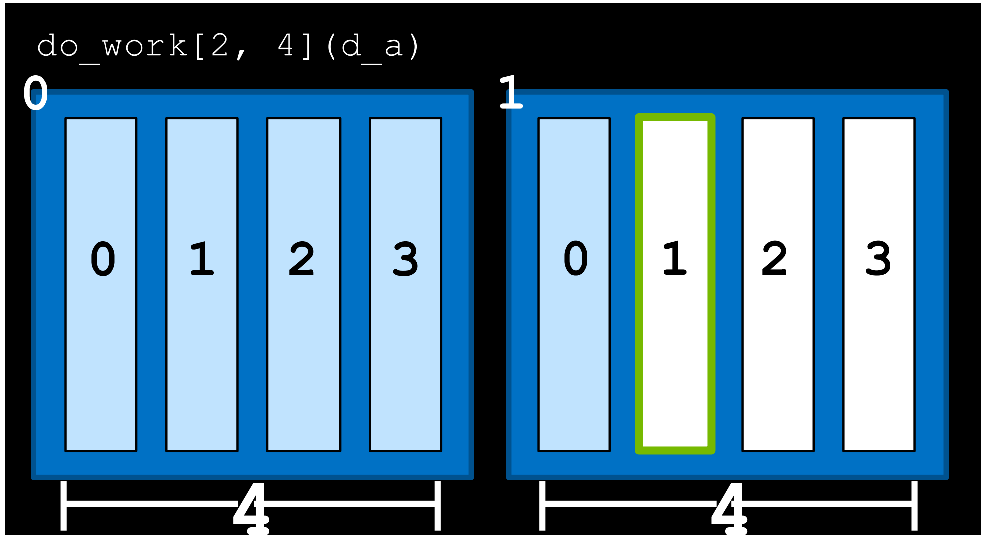
GPU
DATA

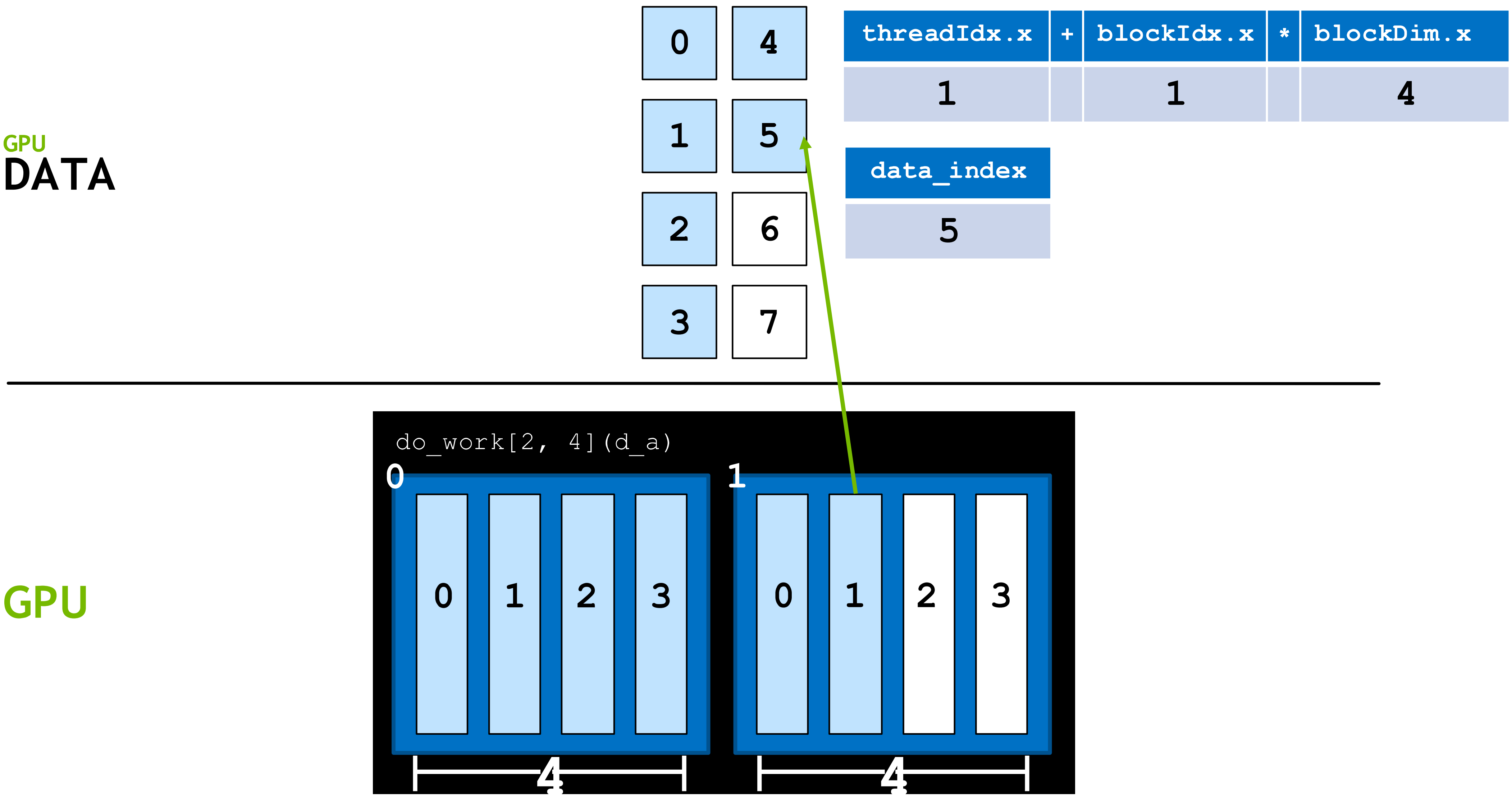


threadIdx.x	+	blockIdx.x	*	blockDim.x
1		1		4

data_index
?

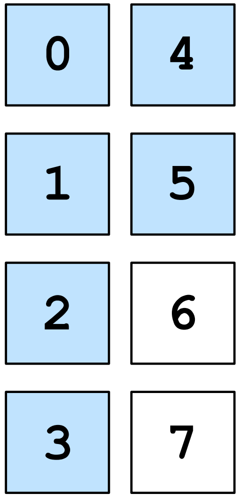
GPU





GPU
DATA
0
1
2
3
4
5
6
7
threadIdx.x
+
blockIdx.x
*
blockDim.x
1
1
4
data_index
5
GPU
do_work[2, 4](d_a)
0
1
0
1
2
3
0
1
2
3
4
4

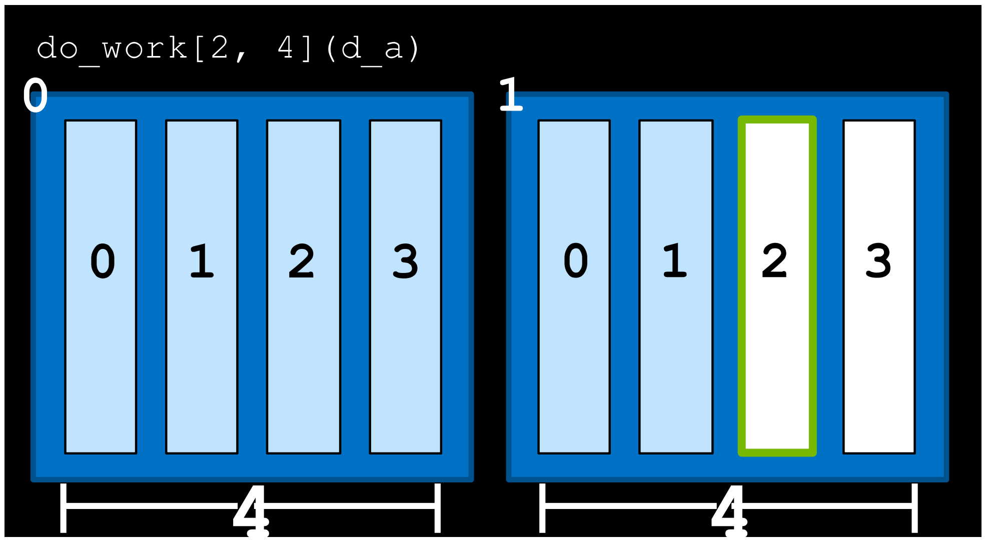
GPU
DATA

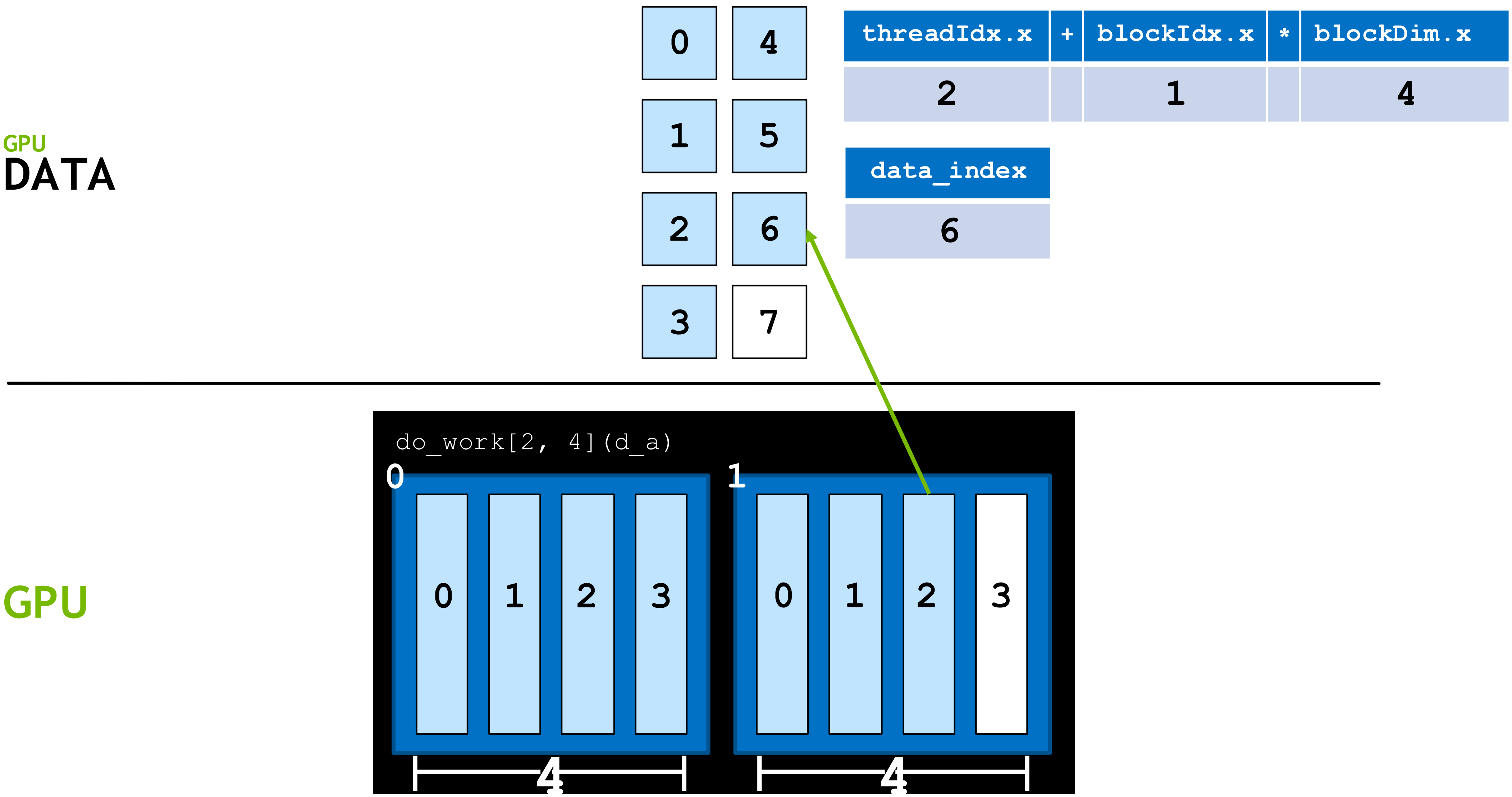


threadIdx.x	+	blockIdx.x	*	blockDim.x
2		1		4

data_index
?

GPU

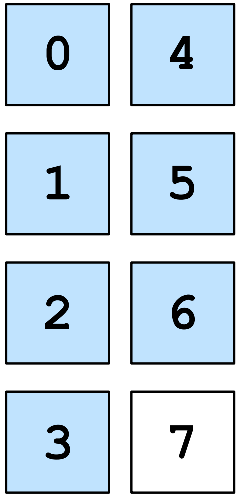




GPU
DATA
0
1
2
3
4
5
6
7
threadIdx.x
+
blockIdx.x
*
blockDim.x
2
1
4
data_index
6
GPU
do_work[2, 4](d_a)
0
0
1
2
3
4
1
0
1
2
3
4

GPU

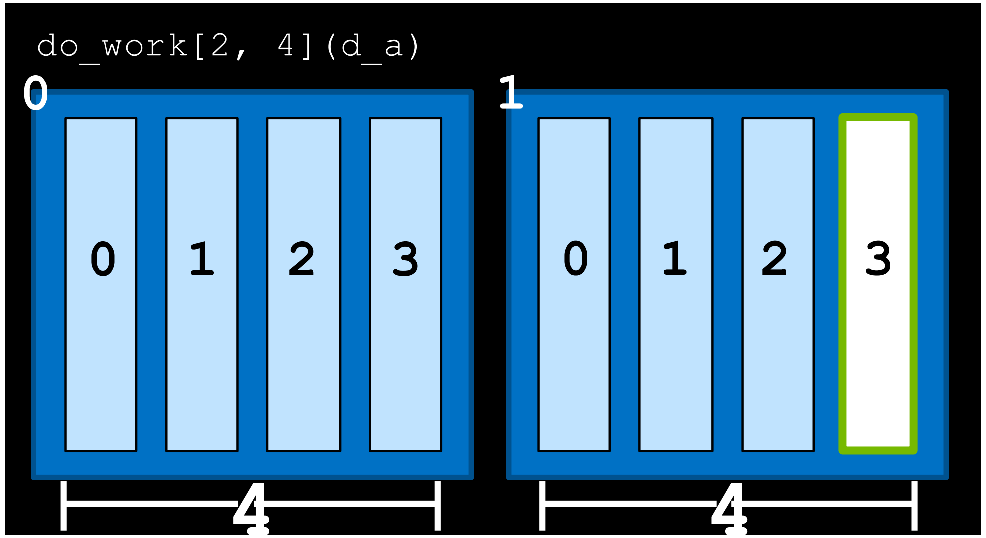
DATA



threadIdx.x	+	blockIdx.x	*	blockDim.x
3		1		4

data_index
?

GPU

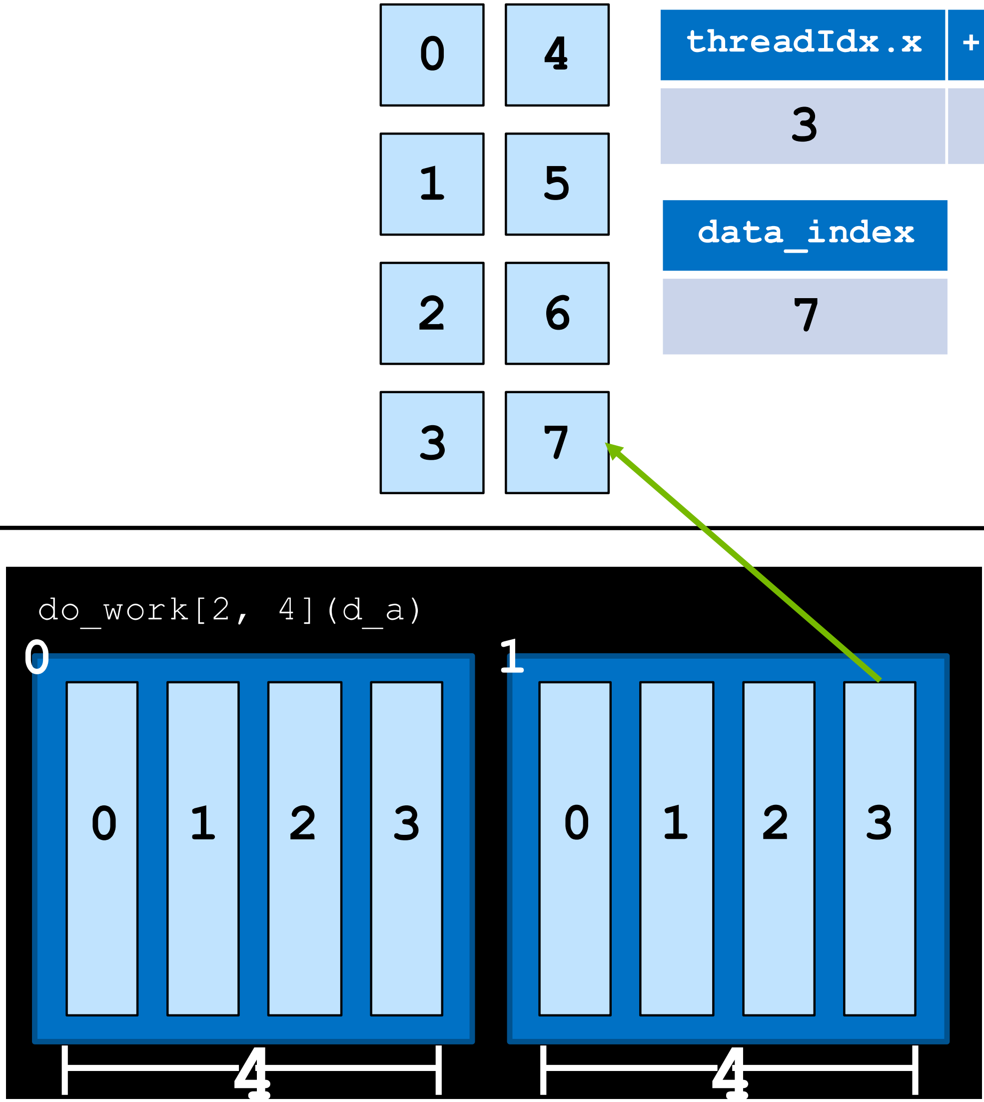


GPU
DATA

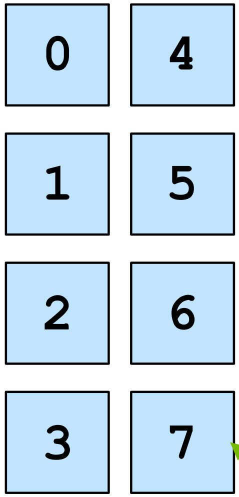
threadIdx.x	+	blockIdx.x	*	blockDim.x
3		1		4

data_index
7

GPU



GPU
DATA

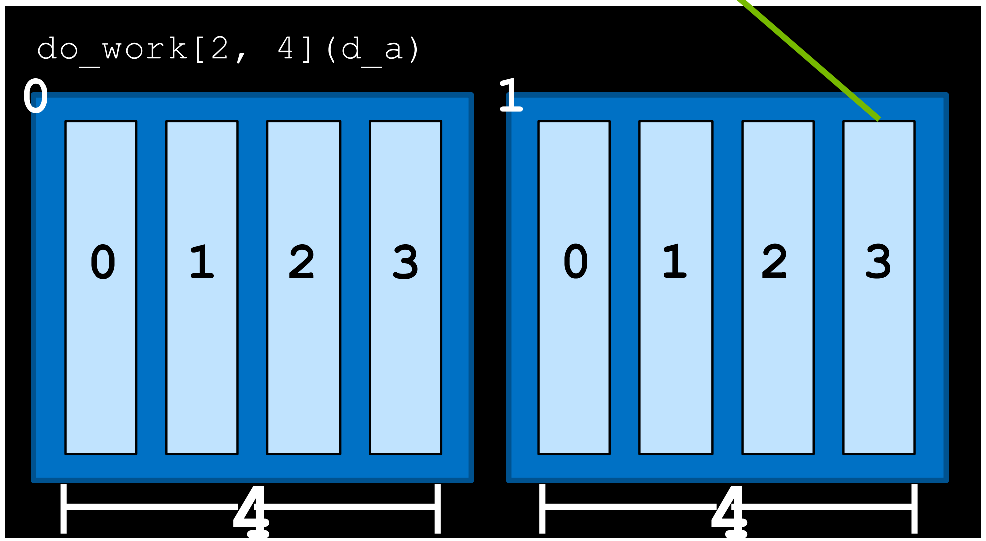


threadIdx.x	+	blockIdx.x	*	blockDim.x
3		1		4

data_index
7
grid(1)
7

As a convenience, Numba provides the `cuda.grid()` function, which will return a thread's unique index in the grid.

GPU



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