

## Introduction

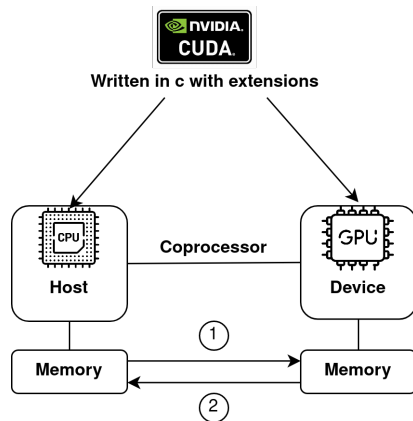
Three traditional ways how designers make computers run faster:

- \* More processors
- \* Faster clocks
- \* More work / clock cycle

CPU	GPU
Complex control hardware	Simpler control hardware
Flexibility and performance	More hardware for computation
Expensive in terms of power	Potentially more power efficient
	More restrictive programming model

Build a Power-Efficient high performance processor:

- **Minimize latency.** Latency is the amount of time to complete a task (seconds). Used in (CPU)
- **Throughput** Is tasks completed per unit time (Jobs/hours). Used in (GPU)



A typical GPU program :

1. CPU allocates storage on GPU (cuda Malloc)
2. CPU copies input data from CPU TO GPU (cudaMemcpy)
3. CPU launches kernels on GPU to process the data (kernel launch)
4. CPU copies results back to CPU from GPU (cudaMemcpy)

## kernel

Kernel look like serial programs. write your program as if it will run on one thread <sup>a</sup>. the GPU will run that program on many threads

**the kernel Launch:**

`Kernel<<<Grid of blocks, Block of threads>>>  
(d_out,d_in)`

Maximum number of threads/block: (older gpus:512 / newer gpus 1024)

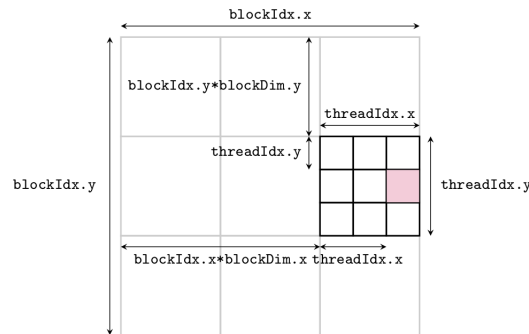
**thread Idx** : thread within block (threadIdx.x ,threadIdx.y)

**blockDim** : size of a block.

**blockIdx** : block with in grid

**gridDim** : size of grid

**Matrix**



- $\text{colonne} = \text{blockIdx.x} * \text{blockDim.x} + \text{threadIdx.x}$
- $\text{ligne} = \text{blockIdx.y} * \text{blockDim.y} + \text{threadIdx.y}$

`kernel<<<<dim3 (bx , by , bz ) , dim3 (tx , ty , tz ) ,  
shmem>>> (...)`

**shmem** : shared memory par block in byets.

<sup>a</sup>one independent path of execution through the code

## Communication Patterns

**MAP:**With Map, you've got many data elements. Such as elements of an array, or entries in a matrix, or pixels in an image. And you're going to do the same function, or computational task, on each piece of data. This means each task is going to read from and write to a specific place in memory. There's a 1 to 1 correspondence between input and output.

**GATHER:**This operation is called a gather because each calculation gathers input data elements together from different places to compute an output result. suppose that you want each thread to compute and store the average across a range of data elements. Say maybe we want to average each set of 3 elements together. In this case each thread is going to read the values from 3 locations in memory and write them into a single place and so on.

**Scatter:** Rather than having each thread read three neighboring elements, average their value, and write a single output result, we can have each thread read a single input result and add 1 3rd of its element's value to the three neighboring elements. So, each of these writes, really be a, an increment operation. we call this scatter because the threads are scattering the results over memory.

**Stencil:**Stencil codes update each element in an array using neighboring array elements in a fixed pattern called the stencil.

**TRANSPOSE:**the transpose operation is where tasks reorder data elements in memory.example: array of structure to structure of array (AoS and SoA).

FOR EXAMPLE:

**Map:**`output[i] = function(input[i])`

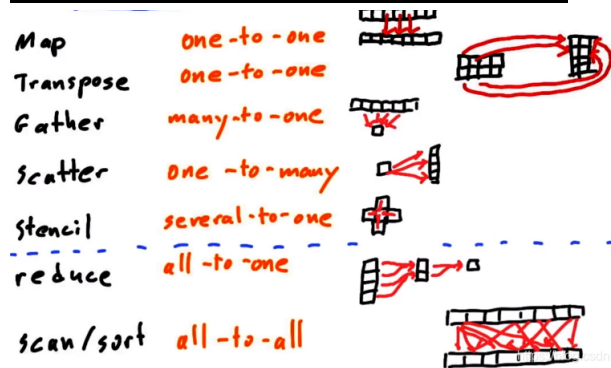
**GATHER:**`output[i] = input[ gatherLoc[i] ]` i.e.

```
if(i % 2)
out[i] = (in[i-1] + in[i] + in[i+1]) / 3.0;
```

**SCATTER:** `output[ scatterLoc[i] ] = input[i]` i.e.

```
if(i % 2 {
out[i - 1] = in[i] * pi;
out[i] = in[i] * pi;
out[i + 1] = in[i] * pi; }
```

## Parallel Communication Patterns Recap



## View of Hardware

GPU: N Streaming Processors (SMs) ( m simple Processors + Memory)

**GPU is responsible for allocating thread blocks to SMs**

All SMs run in parallel and independently

A thread block may not run on more than one SM

## CUDA Programming Features

CUDA Makes Few Guarantees About when and where Thread Blocks will run

### Advantages

- hardware can run things efficiently
- no waiting on slowpokes
- scalability! (same code for different hardwares)

### Consequences:

- no assumptions between blocks to SMs
- no communications between blocks, 'dead lock'

**Dead lock:** 2 computer programs sharing the same resource are effectively preventing each other from accessing the resource

### CUDA guarantees that:

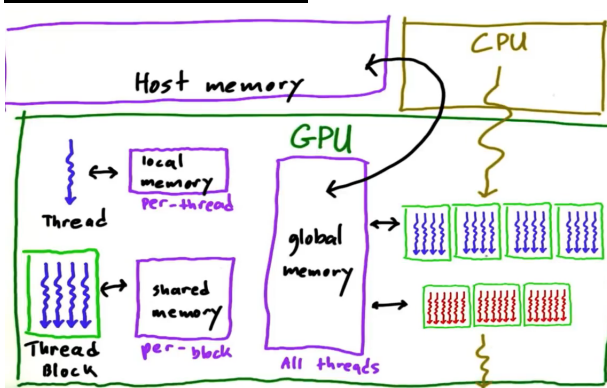
- all threads in a block run on the same sm at the same time
- all blocks in a kernel finish before any blocks from the next kernel run

## Atomic Memory Operations

e.g. `atomicAdd(& g[i], 1);`

guarantees only 1 thread can read-modify-write a variable at the same time

## GPU Memory Model



## Synchronization

**Barrier** – point in the program where threads stop and wait, all threads reach barrier and they can proceed.

```
int idx = threadIdx.x;
__shared__ int array[128];
array[idx] = threadIdx.x;
__syncthreads();
if (idx < 127) {
    int temp = array[idx+1];
    __syncthreads();
    array[idx] = temp;
}
__syncthreads();
```

## Writing Efficient Programs

1. Maximize arithmetic intensity (math/intensity)
- maximize compute ops per thread
- minimize time spent on memory per thread

- move frequently-accessed data to fast memory (local > shared >> global >> CPU memory)
- coalesce global memory accesses, threads read and write contiguous memory locations (larger stride, more memory transactions -> not so good; random -> bad)

2. Avoid thread divergence

## code

Listing 1: Squaring Numbers

```
1 #include <stdio.h>
2 __global__ void square(float *d_out,
3     float *d_in)
4 {
5     int idx = threadIdx.x;
6     float f = d_in[idx];
7     d_out[idx] = f*f;
8 } //end of square kernel
9
10 int main(void)
11 {
12     const int ARRAY_SIZE = 64;
13     const int ARRAY_BYTES = ARRAY_SIZE *
14         sizeof (float);
15     //generate the input array on host
16     //build an array
17     float h_in[ARRAY_SIZE];
18     //convert each element in array to
19     float
20     for (int i = 0; i < ARRAY_SIZE ; i++)
21     {
22         h_in[i] = float(i);
23     } //end of for loop
24     float h_out[ARRAY_SIZE];
25     //declare GPU memory pointers
26     //To declare variable on GPU, you deal
27     with it as pointer
28     float * d_in;
29     float * d_out;
30     //allocate GPU memory
31     cudaMalloc((void **) &d_in,
32         ARRAY_BYTES);
33     cudaMalloc((void **) &d_out,
34         ARRAY_BYTES);
35     //transfer the array to the GPU
36     cudaMemcpy( d_in, h_in, ARRAY_BYTES,
37         cudaMemcpyHostToDevice );
38     //Launch the kernel
39     square<<<1, ARRAY_SIZE>>>> (d_out, d_in
40     );
41     //copy back the result array to CPU
42     cudaMemcpy( h_out, d_out, ARRAY_BYTES,
43         cudaMemcpyDeviceToHost );
44     for (int i = 0; i < ARRAY_SIZE; i++)
45     {
46         printf("%f", h_out[i]);
47     } //end of for loop
48     cudaFree(d_in);
49     cudaFree(d_out);
50     return 0;
51 } //end of main
```

## code

Listing 2: Color to Greyscale Conversion

```

1  __global__
2  void rgba_to_greyscale(const uchar4*
    const rgbaImage, unsigned char* const
    greyImage, int numRows, int numCols)
3  {
4      int y = threadIdx.y + blockIdx.y *
        blockDim.y;
5      int x = threadIdx.x + blockIdx.x *
        blockDim.x;
6      if (y < numRows && x < numCols) {
7          int index = numRows*y + x;
8          uchar4 color = rgbaImage[index];
9          unsigned char grey = (unsigned char)
            (0.299f*color.x + 0.587f*color.y +
            0.114f*color.z);
10         greyImage[index] = grey;
11     }
12 }
13
14 void your_rgba_to_greyscale(const uchar4
    * const h_rgbaImage, uchar4 * const
    d_rgbaImage, unsigned char* const
    d_greyImage, size_t numRows, size_t
    numCols)
15 {
16     //You must fill in the correct sizes
17     //for the blockSize and gridSize
18     //currently only one block with one
19     //thread is being launched
20
21     int blockDim = 32;
22
23     const dim3 blockSize(blockWidth,
        blockDim, 1);
24     int blocksX = numRows/blockWidth+1;
25     int blocksY = numCols/blockWidth+1;
26     const dim3 gridSize( blocksX, blocksY,
        1);
27     rgba_to_greyscale<<<gridSize, blockSize
        >>>(d_rgbaImage, d_greyImage,
        numRows, numCols);
28     cudaDeviceSynchronize();
29     checkCudaErrors(cudaGetLastError());
30 }

```

## code

Listing 3: hello blockIdx

```

1  #include <stdio.h>
2
3  #define NUM_BLOCKS 16
4  #define BLOCK_WIDTH 1
5
6  __global__ void hello()
7  {
8      printf("Hello world! I'm a thread in
        block %d\n", blockIdx.x);
9  }
10
11
12 int main(int argc, char **argv)
13 {
14     // launch the kernel
15     hello<<<NUM_BLOCKS, BLOCK_WIDTH>>>());
16
17     // force the printf(s) to flush
18     cudaDeviceSynchronize();
19
20     printf("That's all!\n");
21
22     return 0;
23 }

```

## code

Listing 4: Using different memory spaces in CUDA

```

1  #include <stdio.h>
2  /* using local memory */
3  __global__ void use_local_memory_GPU(
    float in)
4  {
5      float f; // variable "f" is in
        local memory and private to each
        thread
6      f = in; // parameter "in" is in
        local memory and private to each
        thread
7  }
8  /* using global memory */
9  __global__ void use_global_memory_GPU(
    float *array)
10 {
11     // "array" is a pointer into global
        memory on the device
12     array[threadIdx.x] = 2.0f * (float)
        threadIdx.x;
13 }
14 /* using shared memory */
15 __global__ void use_shared_memory_GPU(
    float *array)
16 {
17     int i, index = threadIdx.x;
18     float average, sum = 0.0f;
19     // __shared__ var are visible to all
        threads in the thread block
20     // and have the same lifetime as the
        thread block
21     __shared__ float sh_arr[128];
22     // here, each thread is responsible
        for copying a single element.
23     sh_arr[index] = array[index];
24     __syncthreads();
25     // find the average of all previous
        elements
26     for (i=0; i<index; i++) { sum +=
        sh_arr[i]; }
27     average = sum / (index + 1.0f);
28     // since array[] is in global memory,
        this change will be seen by the
        host (and potentially
29     // other thread blocks, if any)
30     if (array[index] > average) { array[
        index] = average; }
31     // the following code has NO EFFECT:
        it modifies shared memory, but
32     // the resulting modified data is
        never copied back to global
        memory
33     // and vanishes when the thread block
        completes
34     sh_arr[index] = 3.14;
35 }

```

Listing 5: Using different memory main

```

1 int main(int argc, char **argv)
2 {
3     /* First, call a kernel that shows
4        using local memory */
5     use_local_memory_GPU<<<1, 128>>>(2.0f
6     );
7     /* Next, call a kernel that shows
8        using global memory */
9     float h_arr[128]; // convention: h-
10    variables live on host
11    float *d_arr;      // convention: d-
12    variables live on device (GPU
13    global mem)
14    // allocate global memory on the
15    device, place result in "d_arr"
16    cudaMalloc((void **) &d_arr, sizeof(
17    float) * 128);
18    // now copy data from host memory "
19    h_arr" to device memory "d_arr"
20    cudaMemcpy((void *)d_arr, (void *)
21    h_arr, sizeof(float) * 128,
22    cudaMemcpyHostToDevice);
23    // launch the kernel (1 block of 128
24    threads)
25    use_global_memory_GPU<<<1, 128>>>(
26    d_arr); // modifies the contents
27    of array at d_arr
28    // copy the modified array back to
29    the host, overwriting contents of
30    h_arr
31    cudaMemcpy((void *)h_arr, (void *)
32    d_arr, sizeof(float) * 128,
33    cudaMemcpyDeviceToHost);
34    // ... do other stuff ...
35    /* Next, call a kernel that shows
36       using shared memory*/
37    // as before, pass in a pointer to
38    data in global memory
39    use_shared_memory_GPU<<<1, 128>>>(
40    d_arr);
41    // copy the modified array back to
42    the host
43    cudaMemcpy((void *)h_arr, (void *)
44    d_arr, sizeof(float) * 128,
45    cudaMemcpyHostToDevice);
46    // ... do other stuff ...
47    return 0;
48 }

```