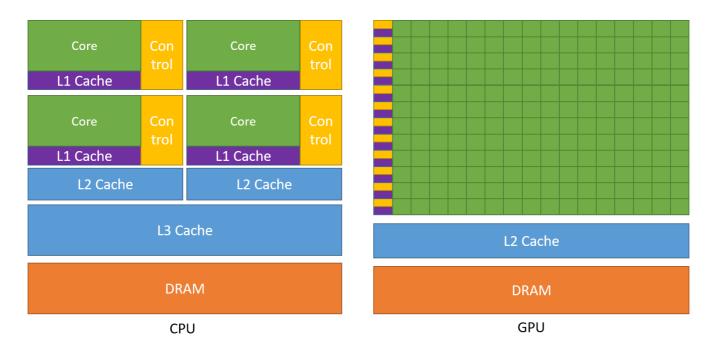
Introduction to CUDA programming

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General GPU architecture

- Many simple cores, organised through several layers of hierarchy, with shared controls
 - RTX 4090: 16384 CUDA cores

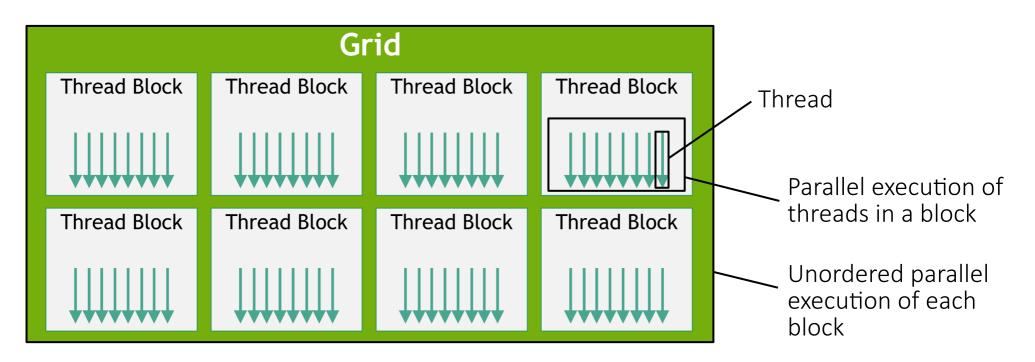


- Efficient for highly/"embarrassingly" parallel tasks
 - Historically for 2D/3D graphics applications
 - GPGU: intensive scientific computing, deep learning...

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CUDA programming model

- CUDA: Compute Unified Device Architecture
 - NVIDIA's parallel computing architecture & API
- High-level CUDA thread hierarchy:
 - Thread: executed sequence of instructions
 - Block: group of multiple threads
 - Grid: set of blocks being executed on the GPU



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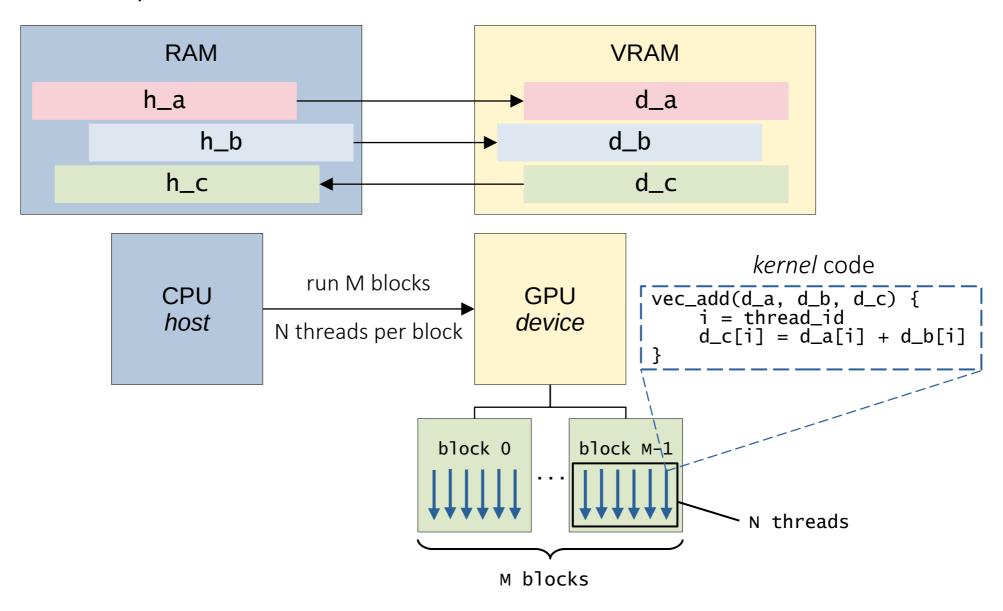
C++ example: vector addition

```
// main.cpp
#include <stdlib.h>
#include <stdio.h>
void add_vec(float *a, float *b, float *c, int N) {
    operations: can be parallelized
}
int main() {
    int N = 32; // vectors of size 32
   float *a = (float*)malloc(N * sizeof(float));
float *b = (float*)malloc(N * sizeof(float));
    float *c = (float*)malloc(N * sizeof(float));
    for(int i = 0; i < N; i++){ // a and b are \{0, 1, ..., N-1\}
        a[i] = (float)i;
        b[i] = (float)i;
    add_{vec}(a, b, c, N); \leftarrow
                                           N sequential operations
    for(int i = 0; i < N; i++){
        printf("%.0f ", c[i]);
                                           c[0] = a[0] + b[0];
                                           c[1] = a[1] + b[1]:
}
```

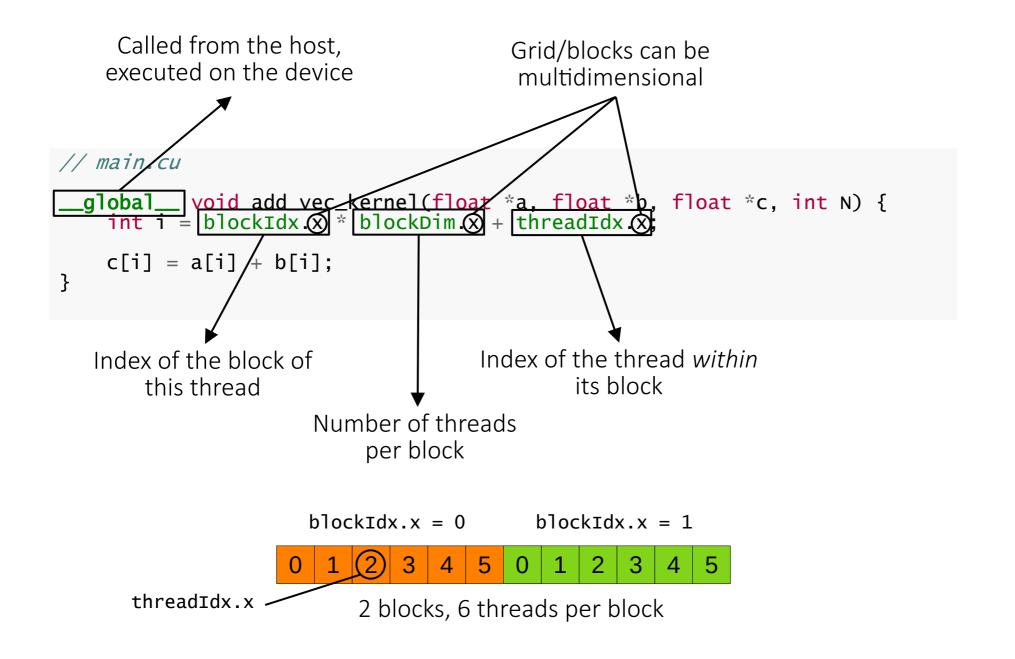
```
$ g++ main.cpp -o main
$ ./main
0 2 4 6 8 10 12 14 16 18 20 22 24 26 28 30 32 34 36 38 40 42 44 46 48 50
52 54 56 58 60 62
```

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 We want to execute add_vec on the GPU in parallel for each index of the arrays



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```
int main() {
    int N = 32;
    float *h_a = (float*)malloc(N * sizeof(float));
    float *h_b = (float*)malloc(N * sizeof(float));
    float *h_c = (float*)malloc(N * sizeof(float));
    for(int i = 0; i < N; i++){
        h_a[i] = (float)i; h_b[i] = (float)i;
    float *d_a, *d_b, *d_c; // device pointers
    // Allocate memory on the device
    cudaMalloc(&d_a, N * sizeof(float));
    cudaMalloc(&d_b, N * sizeof(float));
    cudaMalloc(&d_c, N * sizeof(float));
    // Copy host arrays a and b to the device
    cudaMemcpy(d_a, h_a, N * sizeof(float), cudaMemcpyHostToDevice);
    cudaMemcpy(d_b, h_b, N * sizeof(float), cudaMemcpyHostToDevice);
    // Run 1 block of N = 32 threads executing vec_add_kernel
    int blocks = 1;
    int threads_per_block = N;
    add_vec_kernel<<<bloom{blocks, threads_per_block>>>(d_a, d_b, d_c, N);
    // Execution returns once all threads terminate
    // Copy the result array back from device to host
    cudaMemcpy(h_c, d_c, N * sizeof(float), cudaMemcpyDeviceToHost);
    for(int i = 0; i < N; i++){
        printf("%.0f ", h_c[i]);
    // free memory both from device and host
    free(h_a); free(h_b); free(h_c);
    cudaFree(d_a); cudaFree(d_b); cudaFree(d_c);
}
```

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```
$ nvcc main.cu -o main
$ ./main
0 2 4 6 8 10 12 14 16 18 20 22 24 26 28 30 32 34 36 38 40 42 44 46 48 50
52 54 56 58 60 62
```

- NVCC (Nvidia CUDA Compiler) can interpret mix of C++ and CU files
 - Supports all features of modern C++ in host code (calls g++/cl compiler)
 - Possible object-oriented code, higher order functions in device code, but cannot directly use C++ standard library in a kernel
- Extra libraries provided by CUDA's toolkit:
 - cuda_fp16.h, cuda_bf16.h: defines binary16 (ha1f) and bfloat16 types
 - cuda.h, cuda_runtime.h: driver and runtime libraries used in host-only code (i.e. compiled with g++, cl...)

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CUDA host, global and device functions

- __global__ : called from the host, runs on the device, must be void
- __device___: called from the device, executed on the device, GPUonly functions
- __host__ : called from the host, executed on the host
 - Regular CPU function, qualifier can be omitted

```
__device__ float my_add(float a, float b) {
    return a + b;
}

__global__ void add_vec_kernel(float *a, float *b, float *c, int N) {
    int i = blockIdx.x * blockDim.x + threadIdx.x;

    c[i] = my_add(a[i], b[i]);
}
```

- Limitations:
 - Maximum of 1024 threads per block
 - Grid size limits along each dimension
 - Specifications per compute capabilities

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Total number of threads

- What if you cannot evenly distribute the same number of threads in each block?
 - Make larger blocks or add an extra block
 - Adds more threads than the problem size
 - Must ignore threads which can cause an out-of-bound indexing: "thread check"

```
// main.cu
#include <stdlib.h>
#include <stdio.h>

__global___ void add_vec_kernel(float *a, float *b, float *c, int N) {
    int i = blockIdx.x * blockDim.x + threadIdx.x;

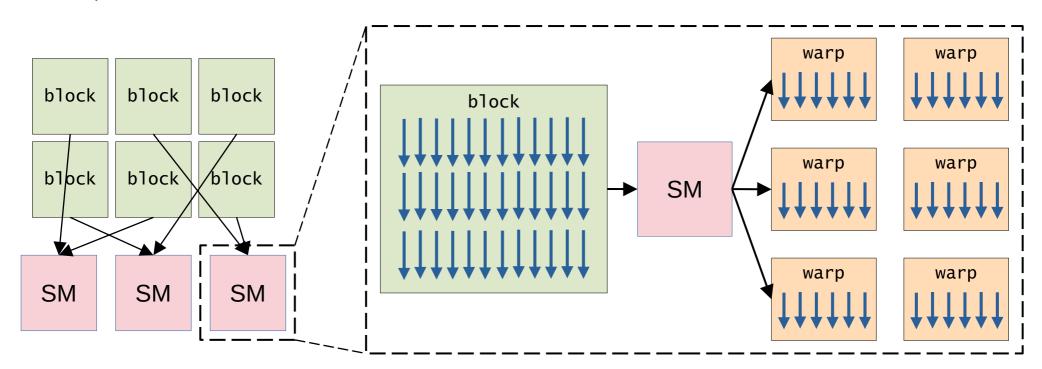
    // Ignore threads out of the expected range
    if(i < N) {
        c[i] = a[i] + b[i];
    }
}</pre>
```

 It is often useful for performance to have block size be a multiple of 32 (see next section on warps)

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Warps and lower-level architecture

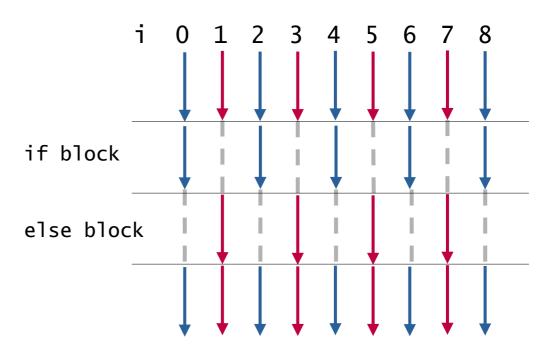
- Each block is assigned to a *streaming multiprocessor* (SM)
- Threads in a block are split in groups of 32 threads (warp)
- Scheduling and ordering of each warp is transparent to the programmer
 - The programmer writes a kernel as if each thread in a block is running in parallel



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Warp execution and branching

- GPU executes threads in Single Instruction, Multiple Threads (SIMT) manner
- Lock-step execution: threads of a warp execute the same instruction at a given instant
- Divergent branching at warp-level can cause slow-downs



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PyTorch and CUDA

- CUDA code is loaded with torch.utils.cpp_extension.load
 - Calls nvcc and creates a python module.
- PyTorch Tensor: represents a multidimensional array
 - 1D vector, 2D matrix, 3D tensor...
- Data is stored as a contiguous (ensure with contiguous()) row-major array of size shape[0] * shape[1] * ... * shape[n] = numel()
- Raw access to the array with data_ptr()
 - e.g: float* array_data = tensor.data_ptr<float>();
 - If tensor.is_cuda(), data_ptr() is a device pointer
 - No memory transfer with cudaMemcpy required
- Call custom kernels directly by passing pointers to raw data

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PyTorch example: square tensor values

```
// square.h
void square_tensor(Tensor input, Tensor output);
// square.cu
  _global___ void square_kernel(float *input, float *output, int N) {
    int i = blockIdx.x * blockDim.x + threadIdx.x;
    if(i < N)
        output[i] = input[i] * input[i];
}
void square_tensor(Tensor input, Tensor output) {
    // Assume input and output have the right shape
    int N = input.numel();
    int threads_per_block = 128;
    // ceiled division, adds an extra block if necessary
    int blocks = N / threads_per_block + (N % threads_per_block > 0);
    float *input_arr = input.data_ptr<float>();
    float *output_arr = output.data_ptr<float>();
    square_kernel<<<bloom{blocks, threads_per_block>>>(input_arr, output_arr);
```

```
// pybind.cpp
#include <pybind11/pybind11.h>
#include "square.h"

PYBIND11_MODULE(TORCH_EXTENSION_NAME, m) {
    m.def("square_tensor", &square_tensor, "Squares a tensor");
}
```

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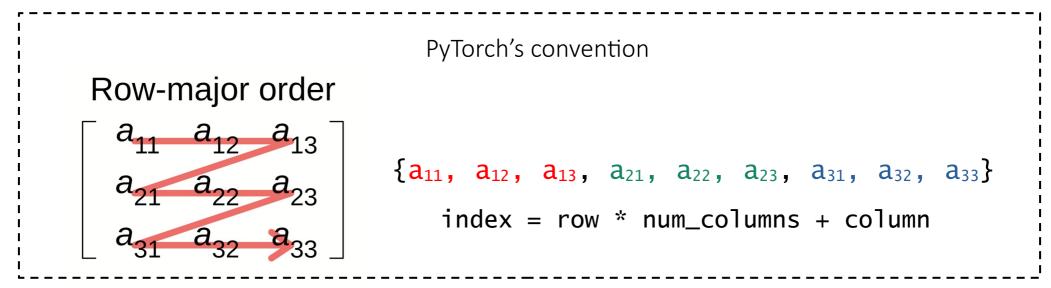
PyTorch example: square tensor values

```
# mv_module.pv
import torch
import torch.utils.cpp_extension as cpp_extension
module = cpp_extension.load(
    name="my_loaded_module",
sources=["square.cu", "pybind.cpp"]
    verbose=False
# define a wrapper around the C++ function
def square(tensor):
    # create the output tensor, must be on the same device
    output = torch.zeros(tensor.shape, device=tensor.device)
    # call the loaded C++ function
    module.square_tensor(tensor, output)
    return output
>>> import torch
>>> from my_module import square
>>>
>>> x = (torch.rand(3, 4)*10).floor()
>>> X
tensor([[7., 7., 9., 0.],
         [6., 6., 3., 9.],
[1., 6., 1., 3.]])
>>> square(x)
tensor([[49., 49., 81., 0.], [36., 36., 9., 81.], [1., 36., 1., 9.]])
```

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Matrix storage

 Matrices (and tensors) are stored as a single contiguous row-major or column-major array



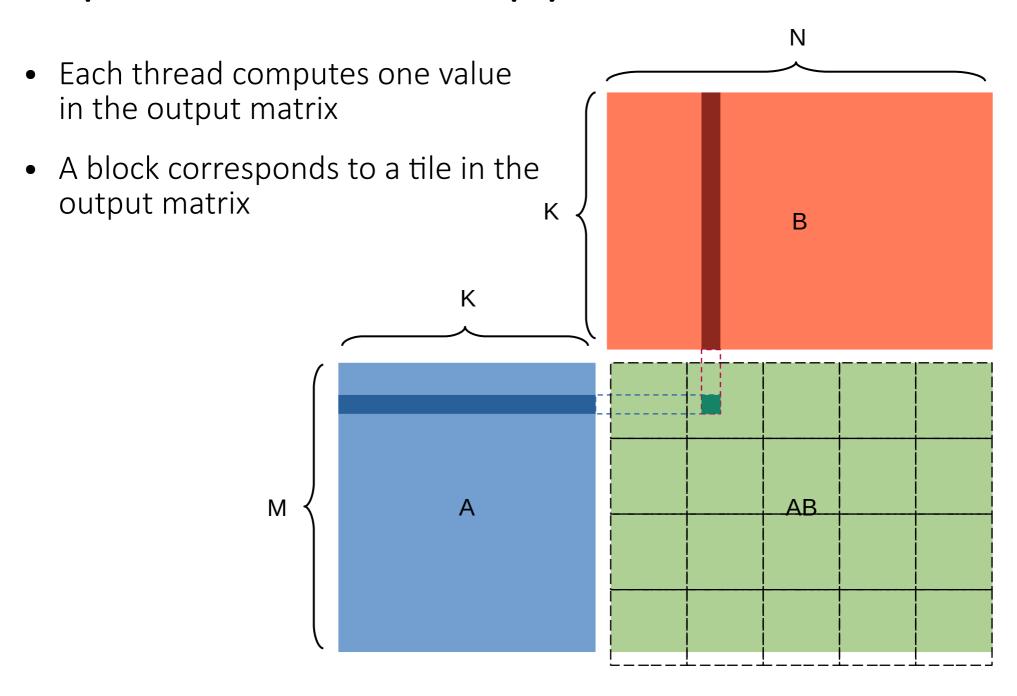
Column-major order

```
\begin{bmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{bmatrix} {a<sub>11</sub>, a<sub>21</sub>, a<sub>31</sub>, a<sub>12</sub>, a<sub>22</sub>, a<sub>32</sub>, a<sub>13</sub>, a<sub>23</sub>, a<sub>33</sub>} index = column * num_rows + row
```

Ordering format can impact performance (memory coalescing)

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Simple CUDA matrix multiply kernel



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Simple CUDA matrix multiply kernel

```
_global___ void matmul_kernel(
    const float* a, // MxK, row-major
    const float* b, // KxN, row-major
    float* out, // MxN, row-major
    int M, int N, int K
    int row = blockIdx.y * blockDim.y + threadIdx.y;
    int col = blockIdx.x * blockDim.x + threadIdx.x;
    if(i >= M || i >= N) return;
    float acc = 0.0f;
    for(int k = 0; k < K; k++) {
        acc += a[row * K + k] * b[k * N + col]
    out[row * N + col] = acc;
}
void matmul(Tensor a, Tensor b, Tensor out) {
    // Assume a, b and out are matrices with matching shapes
    int M = a.size(0);
   int K = a.size(1);
   int N = b.size(1);
    // 2D tiled threads
    dim2 block_size(16, 16); // 16x16 tiles
    dim2 blocks(divceil(N, 16), divceil(M, 16));
    float *a_arr = a.data_ptr<float>();
    float *b_arr = b.data_ptr<float>();
    float *out_arr = out.data_ptr<float>();
   matmul_kernel<<<blooks, block_size>>>(
        a_arr, b_arr, out_arr, M, N, K
    );
```

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Further resources

- https://en.wikipedia.org/wiki/CUDA
- https://docs.nvidia.com/cuda/cuda-c-programming-guide/
- https://developer.nvidia.com/blog/even-easier-introduction-cuda/
- https://docs.nvidia.com/deeplearning/performance/dl-performancematrix-multiplication/index.html

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