GPU Software Hierarchy:
Grids, Blocks, Threads

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GPUs are SIMD Engines
Underneath
Evolution of NVIDIA GPUs
NVIDIA A100 Block Diagram

108 cores on the A100
(Up to 128 cores in the full-blown chip)

40MB L2 cache

https://developer.nvidia.com/blog/nvidia-ampere-architecture-in-depth/
NVIDIA A100 Core

19.5 TFLOPS Single Precision
9.7 TFLOPS Double Precision
312 TFLOPS for Deep Learning (Tensor cores)

https://developer.nvidia.com/blog/nvidia-ampere-architecture-in-depth/
Recall: Latency Hiding via Warp-Level FGMT

- Warp: A set of threads that execute the same instruction (on different data elements)

- Fine-grained multithreading
  - One instruction per thread in pipeline at a time (No interlocking)
  - Interleave warp execution to hide latencies

- Register values of all threads stay in register file

- FGMT enables long latency tolerance
  - Millions of pixels
Recall: Warp Execution

32-thread warp executing \( \text{ADD } A\text{[tid]}, B\text{[tid]} \rightarrow C\text{[tid]} \)

Execution using one pipelined functional unit

Execution using four pipelined functional units

Slide credit: Krste Asanovic
Recall: SIMD Execution Unit Structure

Memory Subsystem

Lane

Registers for each Thread

Registers for thread IDs 0, 4, 8, ...

Registers for thread IDs 1, 5, 9, ...

Registers for thread IDs 2, 6, 10, ...

Registers for thread IDs 3, 7, 11, ...

Functional Unit
Recall: Warp Instruction Level Parallelism

- Can overlap execution of multiple instructions
  - Example machine has 32 threads per warp and 8 lanes
  - Completes 24 operations/cycle while issuing 1 warp/cycle

Slide credit: Krste Asanovic
GPU Programming
Recall: Vector Processor Disadvantages

-- Works (only) if parallelism is regular (data/SIMD parallelism)

++ Vector operations

-- Very inefficient if parallelism is irregular

-- How about searching for a key in a linked list?

To program a vector machine, the compiler or hand coder must make the data structures in the code fit nearly exactly the regular structure built into the hardware. That’s hard to do in first place, and just as hard to change. One tweak, and the low-level code has to be rewritten by a very smart and dedicated programmer who knows the hardware and often the subtleties of the application area. Often the rewriting is

General Purpose Processing on GPU

- Easier programming of SIMD processors with SPMD
  - GPUs have democratized High Performance Computing (HPC)
  - Great FLOPS/$, massively parallel chip on a commodity PC
- Many workloads exhibit inherent parallelism
  - Matrices
  - Image processing
  - Deep neural networks
- However, this is not for free
  - New programming model
  - Algorithms need to be re-implemented and rethought
- Still some bottlenecks
  - CPU-GPU data transfers (PCIe, NVLINK)
  - DRAM memory bandwidth (GDDR5, GDDR6, HBM2)
  - Data layout
Recommended Readings (I)

Recommended Readings (II)

- **CUDA Programming Guide**

**CUDA C++ Programming Guide**

The programming guide to the CUDA model and interface.

**Changes from Version 11.3**
- Added Graph Memory Nodes.
- Formalized Asynchronous SIMT Programming Model.

**1. Introduction**

1.1. The Benefits of Using GPUs

The Graphics Processing Unit (GPU) provides much higher instruction throughput and memory bandwidth than the CPU within a similar price and power envelope. Many applications leverage these higher capabilities to run faster on the GPU than on the CPU (see GPU Applications). Other computing devices, like FPGAs, are also very energy efficient, but offer much less programming flexibility than GPUs.

This difference in capabilities between the GPU and the CPU exists because they are designed with different goals in mind. While the CPU is designed to excel at executing a sequence of operations, called a thread, as fast as possible and can execute a few tens of these threads in parallel, the GPU is designed to excel at executing thousands of them in parallel (amortizing the slower single-thread performance to achieve greater throughput).

The GPU is specialized for highly parallel computations and therefore designed such that more transistors are devoted to data processing rather than data caching and flow control. The schematic Figure 1 shows an example distribution of chip resources for a CPU versus a GPU.
CPU vs. GPU

- Different design philosophies
  - CPU: A few out-of-order cores
  - GPU: Many in-order FGMT cores
GPU Computing

- Computation is **offloaded to the GPU**
- Three steps
  - CPU-GPU data transfer (1)
  - GPU kernel execution (2)
  - GPU-CPU data transfer (3)
Traditional Program Structure

- CPU threads and GPU kernels
  - Sequential or modestly parallel sections on CPU
  - Massively parallel sections on GPU

Serial Code (host)

Parallel Kernel (device)

```
KernelA<<< nBlk, nThr >>>(args);
```

Serial Code (host)

Parallel Kernel (device)

```
KernelB<<< nBlk, nThr >>>(args);
```
Recall: SPMD

- Single procedure/program, multiple data
  - This is a programming model rather than computer organization

- Each processing element executes the same procedure, except on different data elements
  - Procedures can synchronize at certain points in program, e.g. barriers

- Essentially, multiple instruction streams execute the same program
  - Each program/procedure 1) works on different data, 2) can execute a different control-flow path, at run-time
  - Many scientific applications are programmed this way and run on MIMD hardware (multiprocessors)
  - Modern GPUs programmed in a similar way on a SIMD hardware
CUDA/OpenCL Programming Model

- SIMT or SPMD

- Bulk synchronous programming
  - Global (coarse-grain) synchronization between kernels

- The host (typically CPU) allocates memory, copies data, and launches kernels

- The device (typically GPU) executes kernels
  - Grid (NDRange)
  - Block (work-group)
    - Within a block, shared memory, and synchronization
  - Thread (work-item)
Function prototypes

float serialFunction(...);
__global__ void kernel(...);

main()

1) Allocate memory space on the device – cudaMemcpy(&d_in, bytes);
2) Transfer data from host to device – cudaMemcpy(d_in, h_in, ...);
3) Execution configuration setup: #blocks and #threads
4) Kernel call – kernel<<<execution configuration>>>(args...);
5) Transfer results from device to host – cudaMemcpy(h_out, d_out, ...);

Kernel – __global__ void kernel(type args,...)

- Automatic variables transparently assigned to registers
- Shared memory: __shared__
- Intra-block synchronization: __syncthreads();
CUDA Programming Language

- Memory allocation
  
  ```
  cudaMalloc((void**)&d_in, #bytes);
  ```

- Memory copy
  
  ```
  cudaMemcpy(d_in, h_in, #bytes, cudaMemcpyHostToDevice);
  ```

- Kernel launch
  
  ```
  kernel<<< #blocks, #threads >>>(args);
  ```

- Memory deallocation
  
  ```
  cudaFree(d_in);
  ```

- Explicit synchronization
  
  ```
  cudaDeviceSynchronize();
  ```
void vecadd(float* A, float* B, float* C, int N) {
    // Allocate GPU memory
    float *A_d, *B_d, *C_d;
    cudaMalloc((void**)&A_d, N*sizeof(float));
    cudaMalloc((void**)&B_d, N*sizeof(float));
    cudaMalloc((void**)&C_d, N*sizeof(float));

    // Copy data to GPU memory
    cudaMemcpy(A_d, A, N*sizeof(float), cudaMemcpyHostToDevice);
    cudaMemcpy(B_d, B, N*sizeof(float), cudaMemcpyHostToDevice);

    // Perform computation on GPU
    ...

    // Copy data from GPU memory
    cudaMemcpy(C, C_d, N*sizeof(float), cudaMemcpyDeviceToHost);

    // Deallocate GPU memory
    cudaFree(A_d);
    cudaFree(B_d);
    cudaFree(C_d);
}

Slide credit: Izzat El Hajj
Vector Addition (I)

- Our first GPU programming example
- We assign one GPU thread to each element-wise addition
Vector Addition (II)

- The whole set of threads is called a **grid**
- We need a way to assign threads to GPU cores
Vector Addition (III)

- We group threads into blocks

```


```

Block 0  Block 1  Block 2  Block 3
Hardware is **free to schedule** thread blocks.
Launching a Grid

- Threads in the same grid execute the same function known as a kernel

- A grid can be launched by calling a kernel and configuring it with appropriate grid and block sizes

```c
const unsigned int numThreadsPerBlock = 512;
const unsigned int numBlocks = N/numThreadsPerBlock;

vecadd_kernel<<<numBlocks, numThreadsPerBlock>>>(A_d, B_d, C_d, N);
```
void vecadd(float* A, float* B, float* C, int N) {
    // Allocate GPU memory
    float *A_d, *B_d, *C_d;
    cudaMalloc((void**)&A_d, N*sizeof(float));
    cudaMalloc((void**)&B_d, N*sizeof(float));
    cudaMalloc((void**)&C_d, N*sizeof(float));

    // Copy data to GPU memory
    cudaMemcpy(A_d, A, N*sizeof(float), cudaMemcpyHostToDevice);
    cudaMemcpy(B_d, B, N*sizeof(float), cudaMemcpyHostToDevice);

    // Perform computation on GPU
    const unsigned int numThreadsPerBlock = 512;
    const unsigned int numBlocks = N/numThreadsPerBlock;

    vecadd_kernel<<<numBlocks, numThreadsPerBlock>>>(A_d, B_d, C_d, N);

    // Copy data from GPU memory
    cudaMemcpy(C, C_d, N*sizeof(float), cudaMemcpyDeviceToHost);

    // Deallocate GPU memory
    cudaFree(A_d);
    cudaFree(B_d);
    cudaFree(C_d);
}
Sample GPU SIMT Code (Simplified)

CPU code

```c
for (ii = 0; ii < 100000; ++ii) {
}
```

CUDA code

```c
// there are 100000 threads
__global__ void KernelFunction(...) {
    int tid = blockDim.x * blockIdx.x + threadIdx.x;
    int varA = aa[tid];
    int varB = bb[tid];
    C[tid] = varA + varB;
}
```

Slide credit: Hyesoon Kim
Vector Addition Kernel

- It is preceded by the keyword `__global__` to indicate that it is a GPU kernel

- It uses special keywords to distinguish different threads from each other
  - Block index (`blockIdx.x`), block size (`blockDim.x`), thread index (`threadIdx.x`)

```c
__global__ void vecadd_kernel(float* A, float* B, float* C, int N) {
    int i = blockDim.x * blockIdx.x + threadIdx.x;
    C[i] = A[i] + B[i];
}
```
Boundary Conditions

- What if the size of the input is not a multiple of the number of threads per block?
  - Solution: use the ceiling to launch extra threads then omit the threads after the boundary

```c
const unsigned int numBlocks = (N + numThreadsPerBlock - 1)/numThreadsPerBlock;
```

- Kernel code

```c
__global__ void vecadd_kernel(float* A, float* B, float* C, int N) {
    int i = blockDim.x*blockIdx.x + threadIdx.x;
    if(i < N) {
        C[i] = A[i] + B[i];
    }
}
```
Compilation

C/C++ and CUDA code

NVIDIA CUDA Compiler (NVCC)

Host C/C++ Code

Device Just-in-Time Compiler

Host Assembly (e.g., x86, Power, ARM)

CPU

GPU

PTX (Virtual) ISA code

Host C/C++ Code

Device Assembly (e.g., SASS)

Slide credit: Izzat El Hajj
Images are 2D data structures

- height × width
- Image[j][i], where 0 ≤ j < height, and 0 ≤ i < width
Image Layout in Memory

- **Row-major layout**
- $\text{Image}[j][i] = \text{Image}[j \times \text{width} + i]$
Indexing and Memory Access: 1D Grid

- One GPU thread per pixel
- Grid of Blocks of Threads
  - `gridDim.x`, `blockDim.x`
  - `blockIdx.x`, `threadIdx.x`

- `blockIdx.x`
- `threadIdx.x`

- `6 * 4 + 1 = 25`

- `blockIdx.x * blockDim.x + threadIdx.x`
Indexing and Memory Access: 2D Grid

- 2D blocks
  - gridDim.x, gridDim.y

Row = blockIdx.y \times blockDim.y + threadIdx.y
Col = blockIdx.x \times blockDim.x + threadIdx.x

Row = 1 \times 2 + 1 = 3
Col = 0 \times 2 + 1 = 1

Image[3][1] = Image[3 \times 8 + 1]
Recall: From Blocks to Warps

- GPU cores: SIMD pipelines
  - Streaming Multiprocessors (SM)
  - Streaming Processors (SP)

- Blocks are divided into warps
  - SIMD unit (32 threads)
Recommended Readings

  - Chapter 1: Introduction
  - Chapter 2: Data parallel computing
Memory Hierarchy

Grid (Device)

Block (0, 0)

Shared memory

Registers

Thread (0, 0)

Thread (1, 0)

Block (1, 0)

Shared memory

Registers

Thread (0, 0)

Thread (1, 0)

Global / Texture & Surface memory

Constant memory

Host
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