

# GPU Computing

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From programming model to hardware parallelism (🌶️🌶️ & 🔔)

GPU memory model

From programming model to  
hardware parallelism (🌶️🌶️ &  
🔔)

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## Programming Model (1D)

The **same** program  $K$  (kernel) is executed by thousands of threads The only thing that changes is the thread identifier.

$P_1(*args)$   
~~~~~>

$P_2(*args)$   
~~~~~>

$P_3(*args)$   
~~~~~>

$P_4(*args)$   
~~~~~>

$P_5(*args)$   
~~~~~>

$P_6(*args)$   
~~~~~>

$P_7(*args)$   
~~~~~>

$P_8(*args)$   
~~~~~>

Program  $P_i(\text{in}, \text{out})$ :

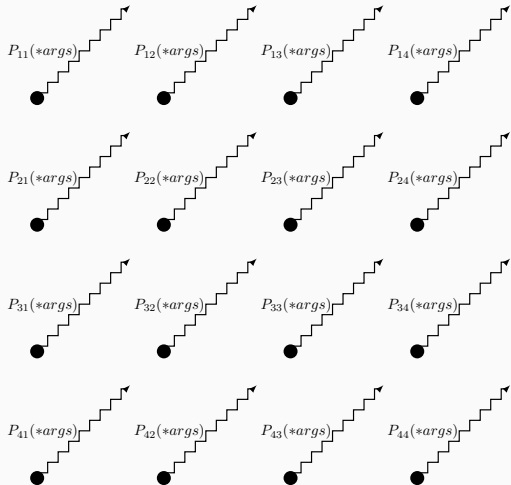
$x \leftarrow \text{in}[i]$

$y \leftarrow \text{Compute something}(x)$

$\text{out}[i] \leftarrow y$

# Programming Model (2D)

The same holds with compute grid in 2D and 3D



```
Program  $P_{ij}$ (in, out):  
   $x \leftarrow \text{in}[i][j]$   
   $y \leftarrow \text{Compute something}(x)$   
   $\text{out}[i][j] \leftarrow y$ 
```

## Thread

- Instance of one *kernel* (list of instructions)
- If *active*, it has a *Program Counter*, *registers*, *private memory*, IO
- Thread ID = ID a *block*

Thread



per-Thread Private  
Local Memory

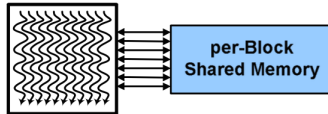


## Block

A set of *threads* that cooperate:

- Synchronisation
- Shared memory
- Block ID = ID in a **grid**

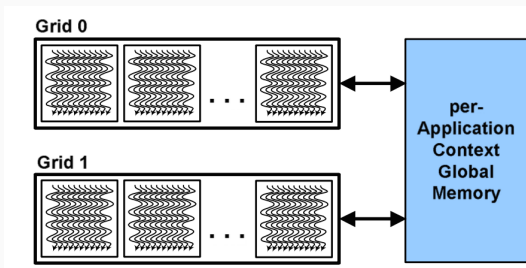
Thread Block



## Grid

Array of blocks executing same *kernel*:

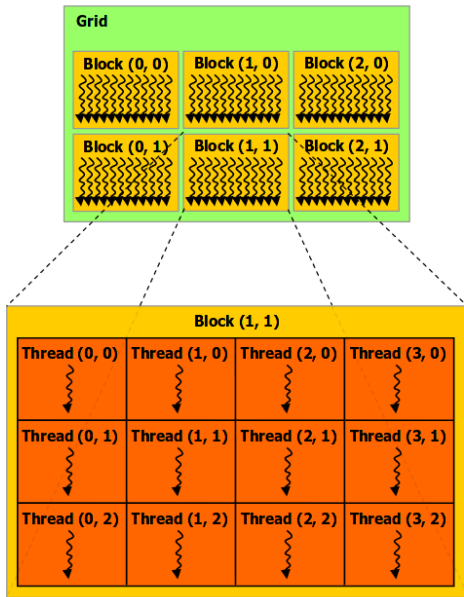
- Access to global GPU memory
- Sync. by stop and start a new kernel



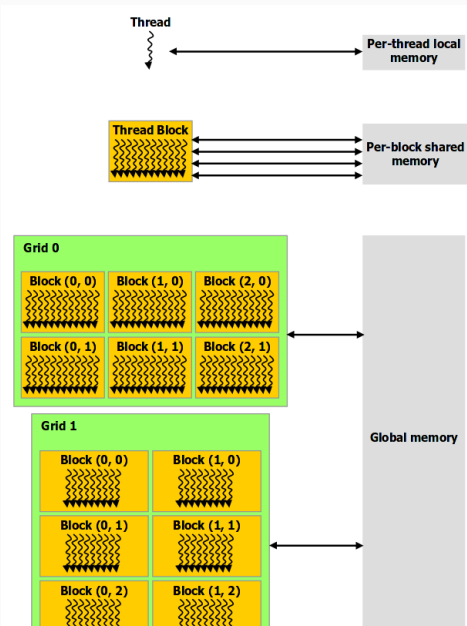


# Programming Model - Summary

## Hierarchy

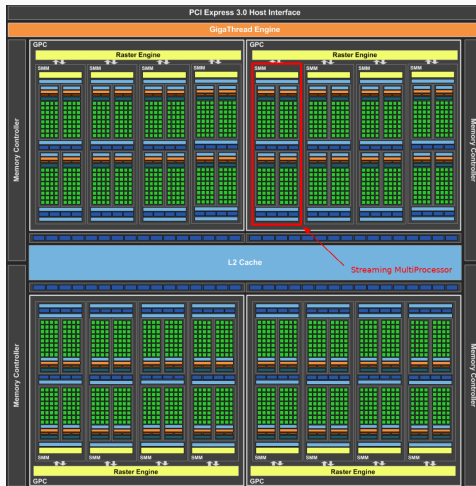


## Memory



# Mapping Programming model to hardware - the SMs

- CUDA's Thread/block/grid is mapped to GPU ( $N^{\circ}\text{Threads} \neq N^{\circ}\text{Cores}$ )



- GTX 980 - 16 Streaming Multi-processors (SM)
- SMs are rather independant

## Mapping Programming model to hardware - the SMs

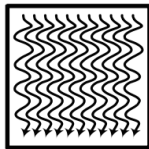
- Any *block* of any *grid* can be mapped to any *SM*



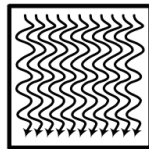
**Thread Block**



**Thread Block**

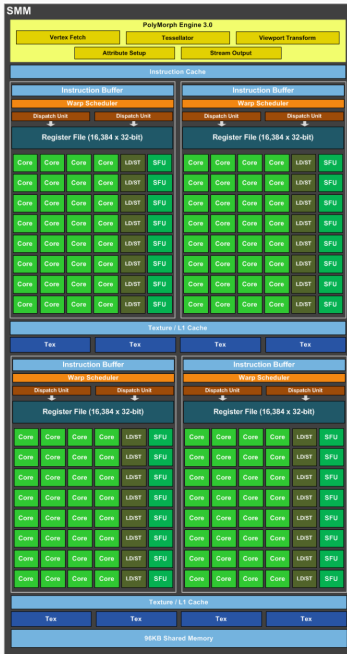


**Thread Block**



- Once *thread block* is affected to a *SM*, it won't move to another one.

# Zoom on the SM



- SM organizes **blocks** into **warps**
- 1 warp = group of 32 threads

GTX 920:

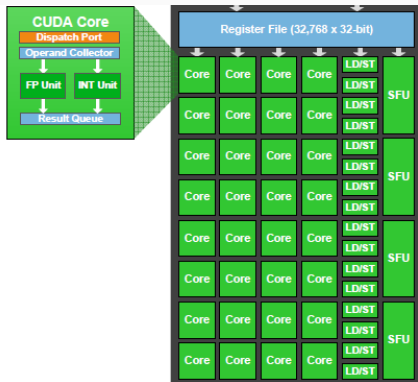
- 128 cores = 4 x 32 cores
- Quad warp scheduler selects **4 warps (TLP)**
- And **2** independent instructions per warp can be dispatched each cycle (**ILP**)

Example:

- 1 (logical) *block* of 96 threads maps to: 3 (physical) *warps* of 32 threads

# Zoom on the CUDA cores

1 core = 1 thread



- A warp executes 32 threads on the 32 CUDA cores
- The threads executes **the same** instruction (DLP)
- All instructions are SIMD  
(width = 32) instructions

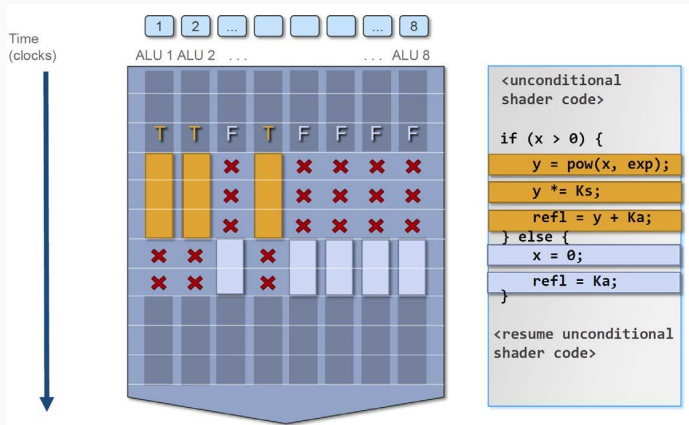
Each core:

- Floating point & Integer unit
- Fused multiply-add (FMA) instruction
- Logic unit
- Move, compare unit
- Branch unit
- The first IF/ID of the pipeline is done by the SM

Warning: SIMT allows to specify the execution and branching behavior of a single thread but maps to SIMD processors!

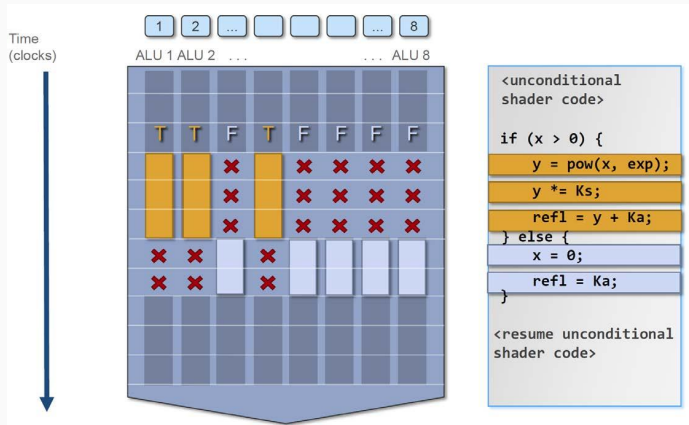
# The SIMT Execution Model on CUDA Cores

- Divergent code paths (branching) pile up!



# The SIMT Execution Model on CUDA Cores

- Divergent code paths (branching) pile up!



A mask allow to dis/activate threads:

|             |   |   |   |   |   |   |   |   |
|-------------|---|---|---|---|---|---|---|---|
| If branch   | 1 | 1 | 0 | 1 | 0 | 0 | 0 | 0 |
| Else branch | 0 | 0 | 1 | 0 | 1 | 1 | 1 | 1 |

## The SIMT Execution Model on CUDA Cores

What is the latency (in term of inst) of this code in the better and worst case ?

```
if a > 0:
    inst-a
    if b > 0:
        inst-b;
    else
        inst-c
else:
    inst-d
```



## The SIMT Execution Model on CUDA Cores

What is the latency (in term of inst) of this code in the better and worst case ?

```
if a > 0:
    inst-a
    if b > 0:
        inst-b;
    else
        inst-c
else:
    inst-d
```

- Best case:  $a > 0$  is false for every thread. For all threads: `inst-d`
- Worst case:  $a > 0$  and  $b > 0$  is true for some but not all threads. For all threads:

```
inst-a
inst-b
inst-c
inst-d
```

## The SIMT Execution Model on CUDA Cores

Loops

```
i = 0
```

```
while i < thread_id:
```

```
    i += 1
```

# The SIMT Execution Model on CUDA Cores

Loops

```
i = 0
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while i < thread_id:
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```
    i += 1
```

Unrollable loops cost = max iterations, ie:

- Keep looping until all threads exit
- Mask out threads that have exited the loop

| Execution trace | T0 | T1 | T2 | T3 |
|-----------------|----|----|----|----|
| i = 0           | 0  | 0  | 0  | 0  |
| i < tid         | 0  | 1  | 1  | 1  |
| i++             | 0  | 1  | 1  | 1  |
| i < tid         | 0  | 0  | 1  | 1  |
| i++             | 0  | 1  | 2  | 2  |
| i < tid         | 0  | 0  | 0  | 1  |
| i++             | 0  | 1  | 2  | 3  |
| i < tid         | 0  | 0  | 0  | 0  |

## GPU memory model

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## Computation cost vs. memory cost

- Power measurements on NVIDIA GT200

|                       | Energy/op (nJ) | Total power (W) |
|-----------------------|----------------|-----------------|
| Instruction Control   | 1.8            | 18              |
| Mult-add 32-wide warp | 3.6            | 36              |
| Load 128B from DRAM   | 80             | 90              |

With the same amount of energy:

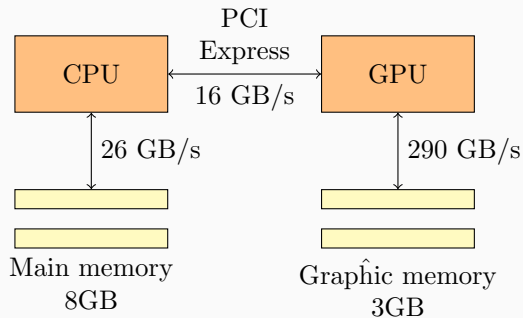
- Load 1 word from external memory (DRAM)
- Compute 44 flops

→ Must optimize memory first

## External memory: discrete GPU

### Classical CPU-GPU model

- Split memory space
- Highest bandwidth from GPU memory
- Transfers to main memory are slower

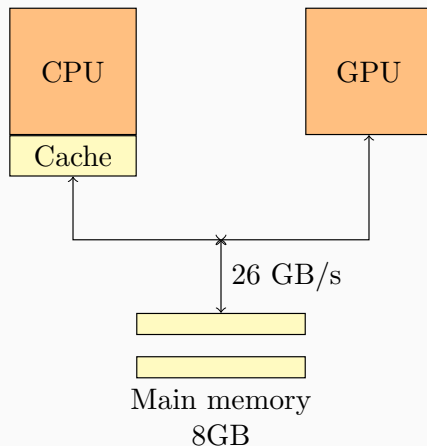


Intel i7 4770 / GTX 780

## External memory: embedded GPU

Most GPUs today:

- Same memory
- May support memory coherence (GPU can read directly from CPU caches)
- More contention on external memory



## GPU: on-chip memory

Cache area in CPU vs GPU:



Figure 1-2. The GPU Devotes More Transistors to Data Processing



# GPU: on-chip memory

Cache area in CPU vs GPU:

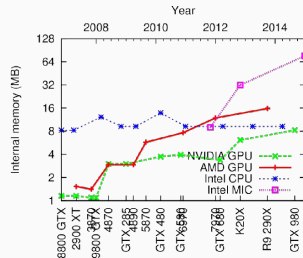


Figure 1-2. The GPU Devotes More Transistors to Data Processing

But if we include registers:

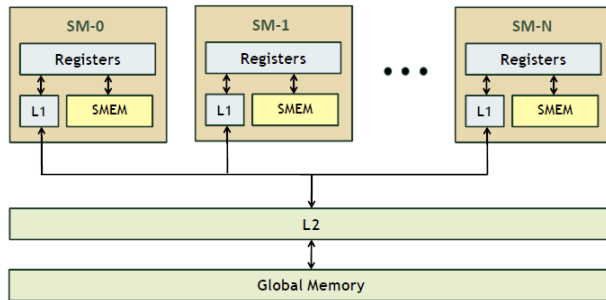
| GPU            | Registers files + caches |
|----------------|--------------------------|
| NVidia Maxwell | 8.3 MB                   |
| AMD Hawaii GPU | 15.8 MB                  |
| Core i7 CPU    | 9.3 MB                   |

|                 | CPU | GPU |
|-----------------|-----|-----|
| Register / Core | 256 | 65K |



→ GPU has many more registers but made of simpler memory

## Memory model hierarchy (hardware)

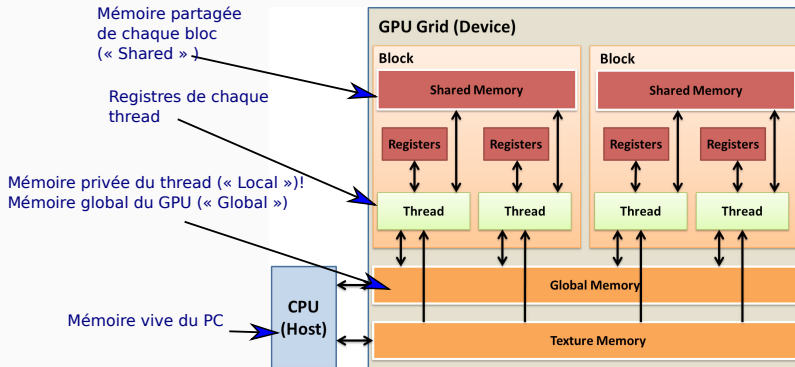


Cache hierarchy:

- Keep frequently-accessed data Core
- Reduce throughput demand on main memory L1
- Managed by hardware (L1, L2) or software (shared memory)

- 
- On CPU, caches are designed to avoid memory latency
  - On GPU, multi-threading deals with memory latency

# Memory model hierarchy (software)



| Memory   | On chip | Cached | Access | Scope              | Lifetime |
|----------|---------|--------|--------|--------------------|----------|
| Register | ✓       | n/a    | RW     | 1 thread           | Thread   |
| Local    | ✗       | ✓      | RW     | 1 thread           | Thread   |
| Shared   | ✓       | n/a    | RW     | All threads block  | Block    |
| Global   | ✗       | ✓      | RW     | All threads + host | Host     |
| Constant | ✗       | ✓      | R      | All threads + host | Host     |
| Texture  | ✗       | ✓      | R      | All threads + host | Host     |

The hierarchical programming model maps to the hierarchical hardware constraints

- Threads inside blocks can synchronise / use shared memory because they are on the same SM
- Threads in the same warp have synchronized execution because they are on the same “SIMD processor”
- Threads in different blocks are hard to synchronize/only communicate with the global memory because they may be on different SMs.

Next time...

CUDA crash course