Modern GPU architectures

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GPUS

- Massively parallel processors
- H100 SXM5
 - 132 Streaming Multiprocessors (SM) per GPU
 - 128 FP32 cores per SM
 - 80GB HBM3 ram
 - 228 KB shared memory / SM

[1] NVIDIA. <u>NVIDIA H100 Tensor Core GPU Architecture</u>. 2022.



GH100 Full GPU with 144 SMs [1]

GPUS - SM

- Streaming Multiprocessors (SM)
 - Individual "CPUs" on chip
 - 4 warps (similar to CPU cores)
- Each warp
 - Tensor Core (matrix multiplier)
 - 32 threads (shared scheduler, dispatcher)

[1] NVIDIA. <u>NVIDIA H100 Tensor Core GPU Architecture</u>. 2022.

GH100 Streaming Multiprocessor (SM) [1]

patch Unit (32 thread/clk) Dispatch Unit (32 thre	iread/clk)
ister File (16,384 x 32-bit) Register File (16,384 :	4 x 32-bit)
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LD/	LD/ LD/ ST ST SF
L0 Instruction Cache L0 Instruction Cac	Cache
p Scheduler (32 thread/clk) Warp Scheduler (32 thr	thread/clk)
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ister File (16,384 x 32-bit) Register File (16,384 x	4 x 32-bit)
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32 FP64 33 ST ST ST ST ST ST ST ST ST ST	LDY LDY ST ST SF
32 FP64 32 FY ST ST ST ST ST ST ST ST	LDY LDY SF
32 FP64 32 ST ST ST ST ST ST ST ST ST	LDY LDY ST ST SF

L1 Instruction Cache

L0 Instruction Cache

SM

L0 Instruction Cache



GPUs in a node

- Compute node
 - 8-16 GPUs per server / node
- Fast / specialized communication between GPUs (NVlink)



Node

GPUs in a datacenter

- Nodes networks in a datacenter
- Up to 40k nodes with 16 GPUs each
 - 0.42 GigaWatt
 - 40% of nuclear power plant, excluding cooling, other hardware
- We have peaked

[1] Meta. <u>Building Meta's GenAl Infrastructure</u>. 2024.[2] <u>https://en.wikipedia.org/wiki/Nuclear_power</u>.





GPUs - Mental model

- Massively parallel processors
 - Intuitions from CPUs and theoretical CS are often wrong
 - Nearly endless compute
 - On a restricted set of operations
 - Limited memory and memory bandwidth



GH100 Full GPU with 144 SMs [1]

GPUs - Mental model A simple example

- You are given a series of numbers ${\bf X}$ and a **fixed** window size W
- Find the maximum number value for all possible windows
 - $e_i = \max(x_i, x_{i+1}, \dots, x_{i+W-1})$
- What deep learning operation is this?

X 1	X 2	X 3	X 4	X 5	X 6



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```
maxpool_1d_heap(x: torch.Tensor, window_size: int):
def
    """A windowed maximum pooling operation for 1D
tensors."""
    output = x_new_zeros(x_size(0) - window_size + 1)
    <u>h = []</u>
    for i in range(x.size(0)):
```

```
output[i - window_size + 1] = -h[0][0]
return output
```

Compute: $O(|\mathbf{x}| \log W)$







GPUs - Mental model A simple example in CUDA

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- What deep learning operation is this?

X 1	X 2	X 3	X 4	X 5	X6
		~3	~4	X 5	70

Compute: $O(|\mathbf{x}| W)$ Memory access: $O(|\mathbf{x}| W)$





GPUs - Mental model A simple example in CUDA

- You are given a series of numbers **X** and a **fixed** window size W
- Find the maximum number value for all possible windows
 - $e_i = \max(x_i, x_{i+1}, \dots, x_{i+W-1})$
- What deep learning operation is this?

X 1	X 2	X 3	X 4	X 5	X6
		~3	~4	X 5	70

Compute: $O(|\mathbf{x}| W/G)$ Memory access: $O(|\mathbf{x}| W/G)$



GPUs - Mental model A simple example in CUDA

- You are given a series of numbers **X** and a **fixed** window size W
- Find the maximum number value for all possible windows
 - $e_i = \max(x_i, x_{i+1}, \dots, x_{i+W-1})$
- What deep learning operation is this?

X 1	X 2	X 3	X 4	X 5	X 6

Compute: $O(|\mathbf{x}| W)$ Memory access: $O\left(|\mathbf{x}|\frac{W}{S}\right)$ S: shared memory size



GPUs - Mental model What have we learned?

- Memory access matters
 - Reads from global memory are expensive
 - Computation is cheap

X 1	X 2	X 3	X 4	X 5	X 6



GPUs - Mental model The secret solution

- $e_i = \max(x_i, x_{i+1}, \dots, x_{i+W-1})$
- $e_i = \max\left(\max(x_i, \dots, x_K), \max(x_{K+1}, \dots, x_{i+W-1})\right)$
- $e_{i+1} = \max\left(\max(x_{i+1}, \dots, x_K), \max(x_{K+1}, \dots, x_{i+W})\right)$

X 1	X 2	X 3	X 4	X 5	X 6
		~3	~4	X 5	70

Compute: $O(|\mathbf{x}|)$ Memory access: $O(|\mathbf{x}|)$



GPUs - Memory Bandwidth

- Node to node communication
 - RDMA/IB: 50GB / s
- GPU to GPU communication (within node)
 - NVLink: 900 GB / s
- GPU memory bandwidth
 - HBM3->shared mem: 3.35 TB / s
- Peak flops: 130-1000 teraFLOPS @ BF16

[1] NVIDIA. <u>NVIDIA H100 Tensor Core GPU Architecture</u>. 2022.



Modern GPU architectures

- Near infinite compute
- Memory bandwidth and size limits
 - Order of magnitude slower
 GPU -> Node -> Datacenter
- Approaching limits of power consumption, and physical limits in manufacture



GH100 Full GPU with 144 SMs [1]

References

- [1] NVIDIA. NVIDIA H100 Tensor Core GPU Architecture. 2022. (link)
- [2] Meta. Building Meta's GenAl Infrastructure. 2024 (link)