Advanced Computer Architecture
高 级 计 算 机 体 系 结 构

第7讲： DLP and GPU (2)

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DCS5367, 11/16/2021

Example: Putting Together

```
#include "hip/hip_runtime.h"
int main() {
  int N = 1000;
  size_t Nbytes = N*sizeof(double);
  double *h_a = (double*) malloc(Nbytes);  //host memory
  double *d_a = NULL;
  HIP_CHECK(hipMalloc(&d_a, Nbytes));
  …
  HIP_CHECK(hipMemcpy(d_a, h_a, Nbytes, hipMemcpyHostToDevice));   //copy data to device

  hipLaunchKernelGGL(myKernel, dim3((N+256-1)/256,1,1), dim3(256,1,1), 0, 0, N, d_a); //Launch kernel
  HIP_CHECK(hipGetLastError());

  HIP_CHECK(hipMemcpy(h_a, d_a, Nbytes, hipMemcpyDeviceToHost))
  …
  free(h_a);                //free host memory
  HIP_CHECK(hipFree(d_a));   //free device memory
}
```

```
__global__ void myKernel(int N, double *d_a) {
  int i = threadIdx.x + blockIdx.x*blockDim.x;
  if (i<N) {
    d_a[i] *= 2.0;
  }
}
```

```
#define HIP_CHECK(command) {                      \
  hipError_t status = command;                    \
  if (status!=hipSuccess) {                       \
    std::cerr << "Error: HIP reports "            \
              << hipGetErrorString(status)  \
              << std::endl;                       \
    std::abort(); } }
```

Device Management

- Host can query *number* of devices visible to system:

```
int numDevices = 0;
hipGetDeviceCount(&numDevices);
```

- Host tells the runtime to issue instructions to a *particular* device:

```
int deviceID = 0;
hipSetDevice(deviceID);
```

- Host can query what device is currently *selected*:

```
hipGetDevice(&deviceID);
```

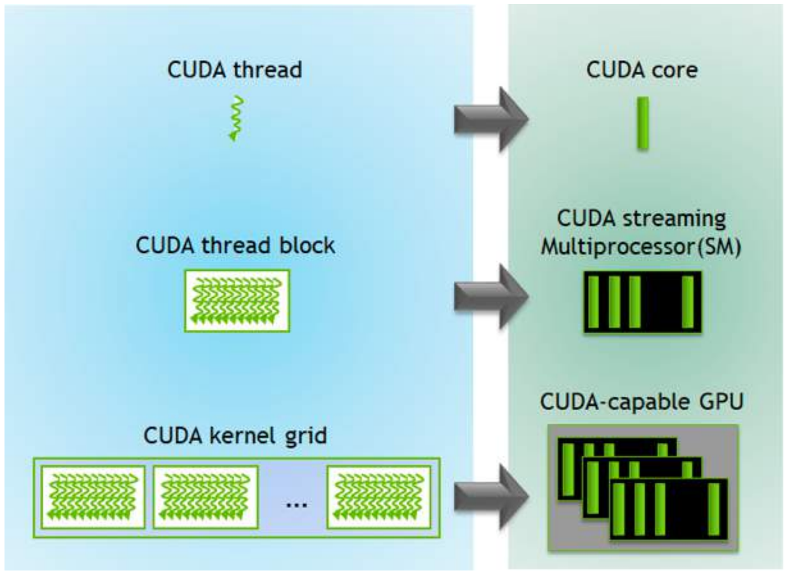
- The host can also query a device's *properties*:

```
hipDeviceProp_t props;
hipGetDeviceProperties(&props, deviceID);
```

hipDeviceProp_t is a struct that contains useful fields like the device's name, total VRAM, clock speed, and GCN architecture.

Map Kernel to Hardware[映射]

- Blocks are dynamically scheduled onto compute units (CUs) SM for Nvidia
  - All threads in a block execute on the same CU a.k.a., workgroup
  - Threads in block share LDS memory and L1 cache SMEM for Nvidia
- Blocks are further divided into wavefronts
  - A group of 32 or 64 threads warp for Nvidia
  - Wavefronts execute on SIMD units



SIMD lane
(streaming processor)

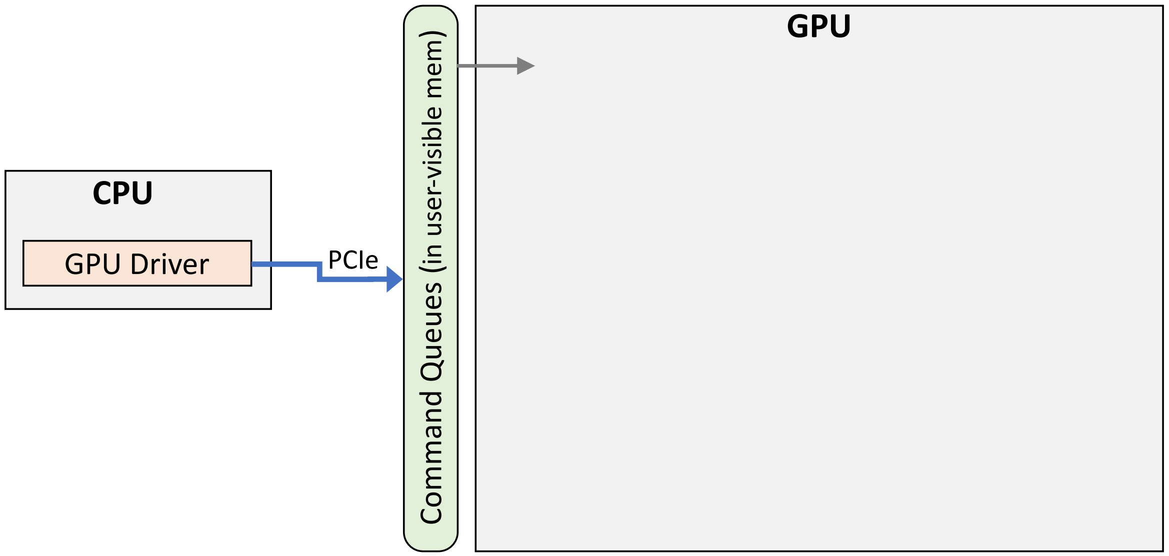
Compute unit

GPU

CPU-GPU

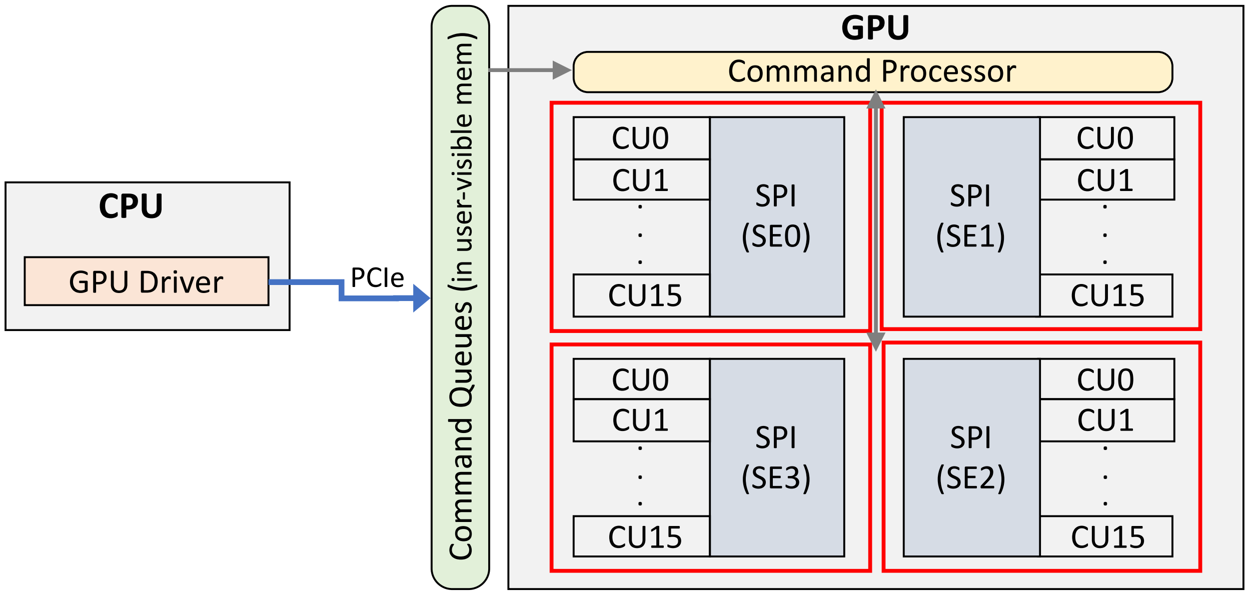
- CPU communicates kernels to GPUs via PCIe
  - Kernel code object is filled into a dispatch *packet*
  - Next, the packet is placed into a *queue*, which is allocated by runtime and associated with a GPU **stream for Nvidia**
  - The *GPU* is then signaled to process packets from the queue
  - When kernel is finished, *CPU* is notified with an interrupt

TIP:
Task
==
Command
==
Packet
==
Kernel



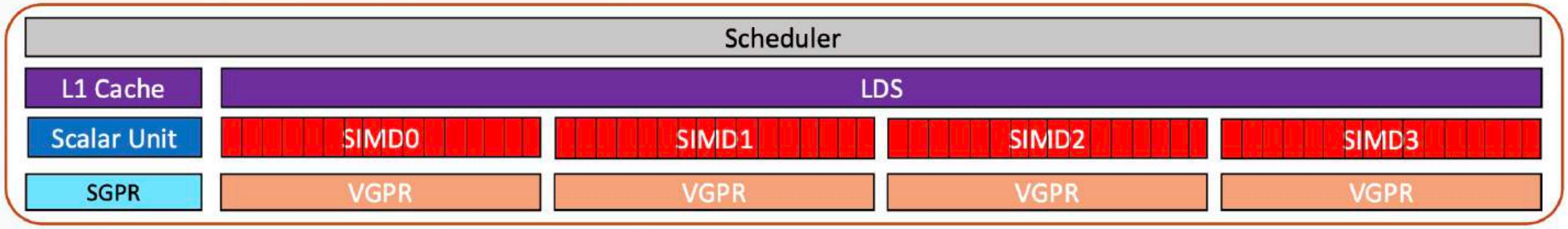
GPU Structure[内部架构]

- Command processor (CP)
  - Forefront hardware component of a GPU to receive kernels
- Shader processor inputs (SPI)
  - Receives WGs from the CP **Blocks/CTAs for Nvidia**
- Compute unit (CU) **SM for Nvidia**
  - Fundamental compute component



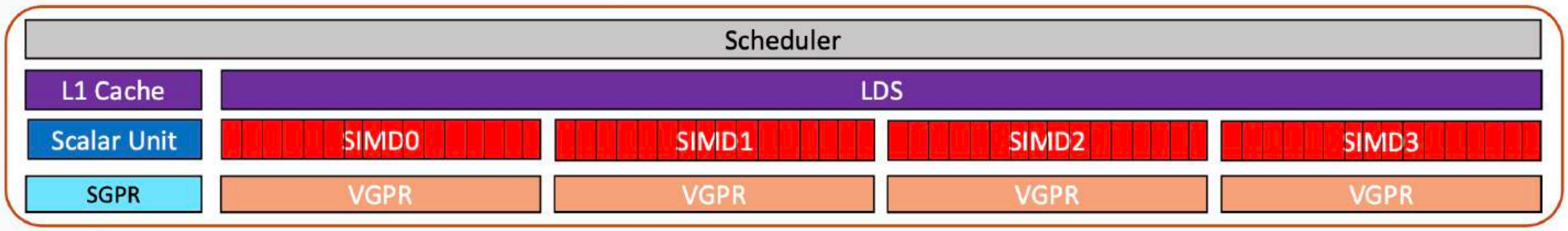
Compute Unit

- Scheduler[调度器]
  - Manage the wavefronts execution among the SIMDs
- Compute[计算]
  - SIMD: for vector processing (a.k.a., vector units, VALUs)[向量单元]
    - Is of 16 lanes in GCN, thus simultaneously executing a single operation among 16 threads
    - Has its own PC and instruction buffer (IB) for 10 WFs
  - Scalar unit[标量单元]
    - Shared by all threads in each WF, accessed on a per-WF level
    - Used for control flow, pointer arithmetic, loading a common value, etc.



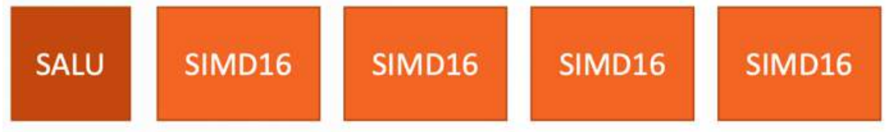
Compute Unit (cont.)

- GPRs[通用寄存器]
  - VGPR: vector general purpose register file
    - 4x 64KB (256KB total)
    - A maximum of 256 total registers per SIMD lane – each register is 64x 4-byte entries
  - SGPR: scalar general purpose register file
    - 12.5KB per CU
- L1 cache: 16KB[一级缓存]
- LDS: local data share (or, shared memory)[片上共享存储]
  - Enables data share between threads of a block

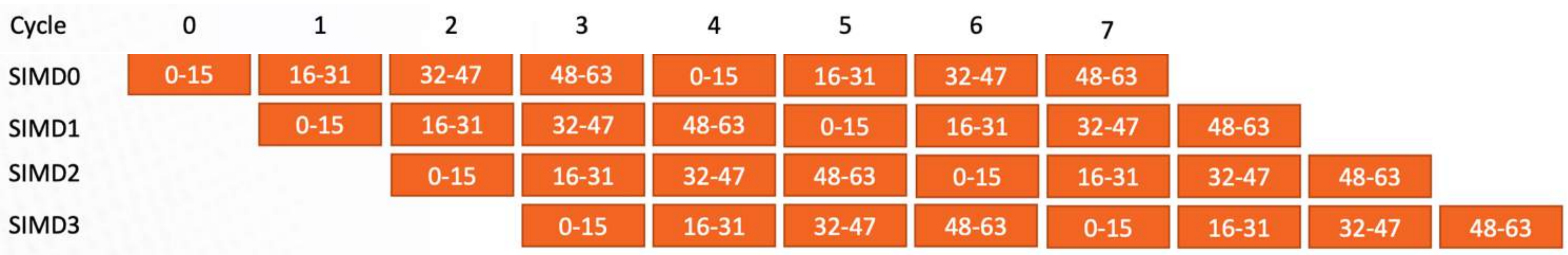


Compute Unit (cont.)

- At each clock, waves on *1 SIMD* unit are considered for execution (Round Robin scheduling among SIMDs)
- Each wave is assigned to one SIMD16, up to *10 waves* per SIMD16 (*math: 4 x 10 x 64 = 2560 threads*)
- Each SIMD16 issues 1 instruction every 4 cycles
- Vector instructions throughput is 1 every 4 cycles



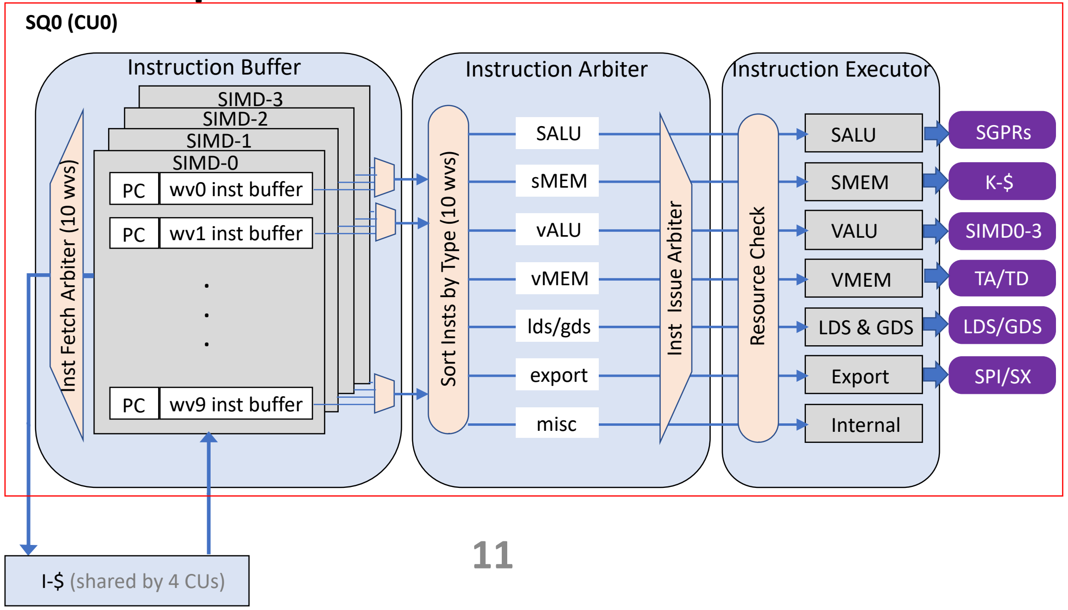
1 every cycle in AMD next generation and Nvidia



Cycle	0	1	2	3	4	5	6	7			
SIMD0	0-15	16-31	32-47	48-63	0-15	16-31	32-47	48-63			
SIMD1		0-15	16-31	32-47	48-63	0-15	16-31	32-47	48-63		
SIMD2			0-15	16-31	32-47	48-63	0-15	16-31	32-47	48-63	
SIMD3				0-15	16-31	32-47	48-63	0-15	16-31	32-47	48-63

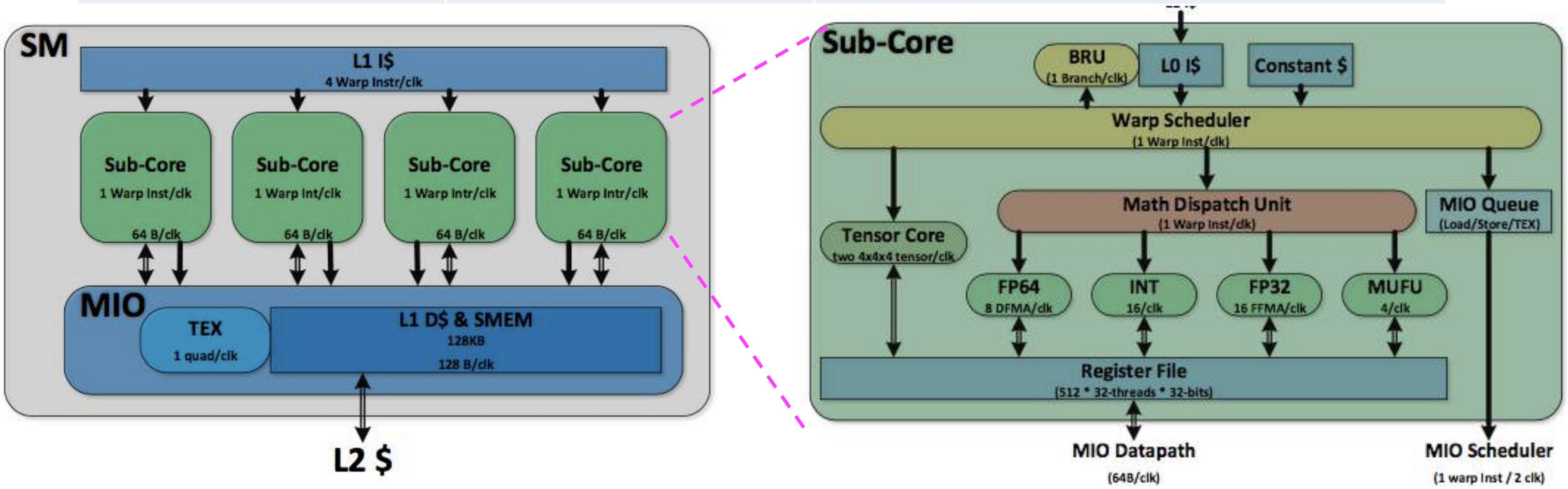
Instruction Execution[指令执行]

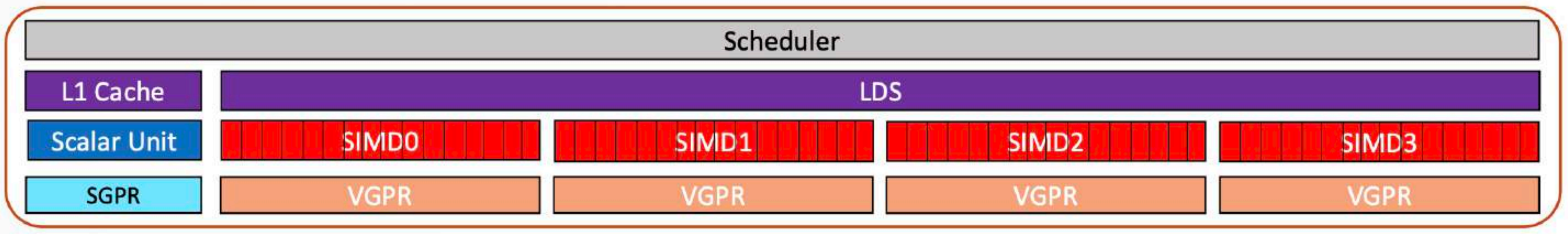
- **Instruction buffer** (IB): each cycle, the 10 wvs of the selected SIMD compete for instruction fetch (oldest wins)
- **Instruction arbiter** (IA): arbitrates multi wvs which want to execute the same type of instructions
- **Instruction executor** (IE): multiple execution units running in parallel; only one instruction of each type can be issued at a time per SIMD



Nvidia SM

Level	Nvidia	AMD
Thread	CUDA core	Streaming processor / SIMD lane
Warp/wavefront	SM sub-partition	SIMD unit
Block/workgroup	SM	Compute unit
All threads	GPU device	GPU device



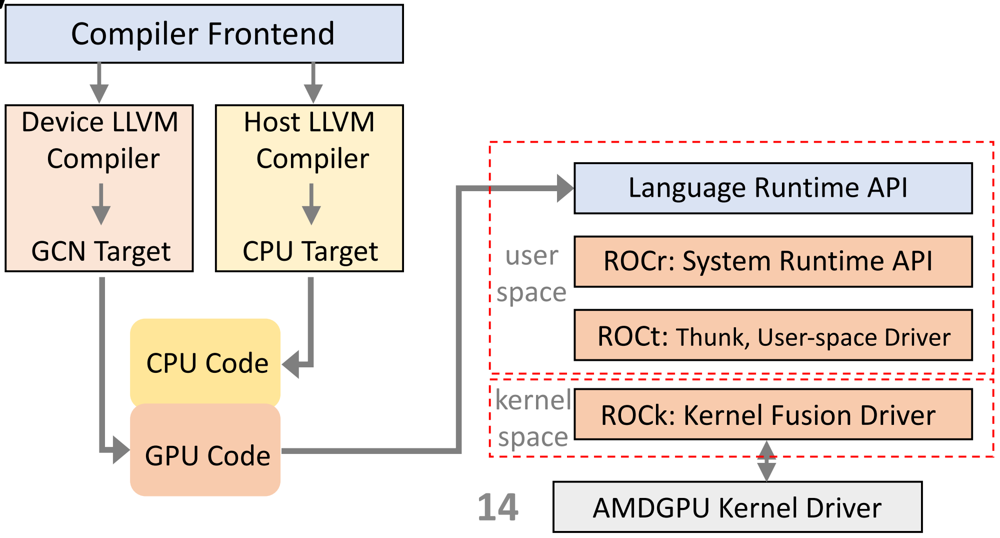


Terminology[术语]

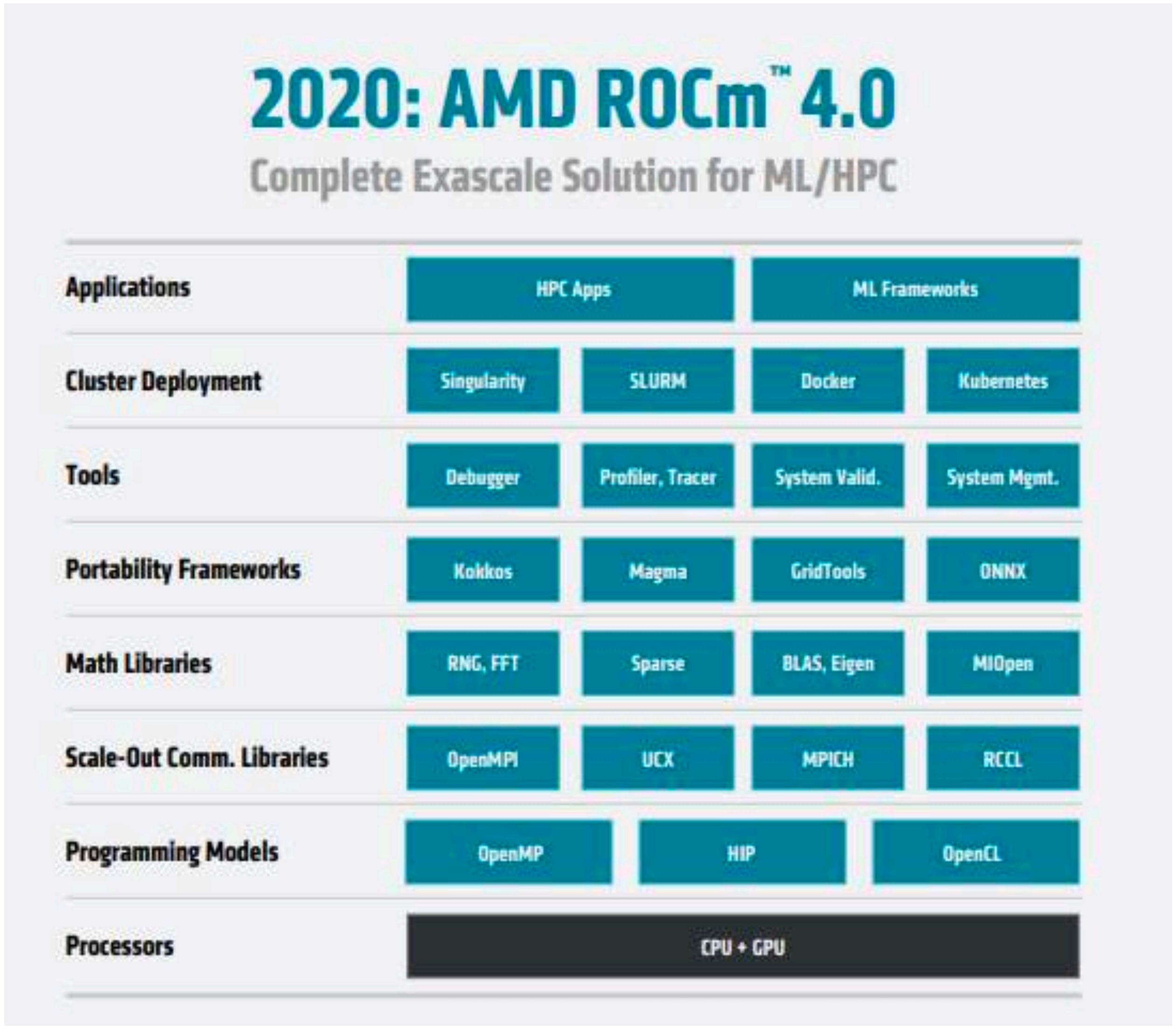
Nvidia	AMD	Note
Thread Block (TB) / Cooperative Thread Array (CTA)	Workgroup (WG)	Basic workload unit assigned to an SM or CU. Each kernel is split into multiple CTAs, and the #CTAs is controlled by the application. Typically, hw limits 1024 threads per block.
Warp	Wavefront (wave/WF/WV)	A group of threads (e.g., 32 for NV, 64 for AMD) executing in lockstep (i.e., run the same inst, follow the same control-flow path). #WFs/WG is chosen by developers.
Thread	Work-item(WI)/thread	A basic element to be processed.
GPU Processing Cluster (GPC)	Shader Engine (SE)	A collection of CUs organized into one or two SHs.
Texture Processing Cluster (TPC)	Shader Array (SH)	A group made up of several SMs or CUs.
Stream Multiprocessor (SM) / Multiprocessor	Compute Unit (CU)	Fundamental unit of computation, replicated multiple times on a GPU.
Sub-core/partition	SIMD	A group of cores to execute one warp/wave.
Stream Processor (SP) / CUDA Core / FPxx Core	Stream Processor / SIMD Lane / VALU Lane	A parallel execution lane comprising an SM or CU.

Software Stack[软件栈]

- Radeon Open Compute platform (ROCm)
  - AMD's open-source software stack
- Multiple layers
  - **Language runtime**: language-specific runtime
  - **ROCr**: user-level language-agnostic runtime
  - **ROCt**: user-space driver talking to the lower-level ROCk
  - **ROCk**: kernel driver to initialize and register with CP the queues allocated by runtimes



ROCm



2020: AMD ROCm™ 4.0

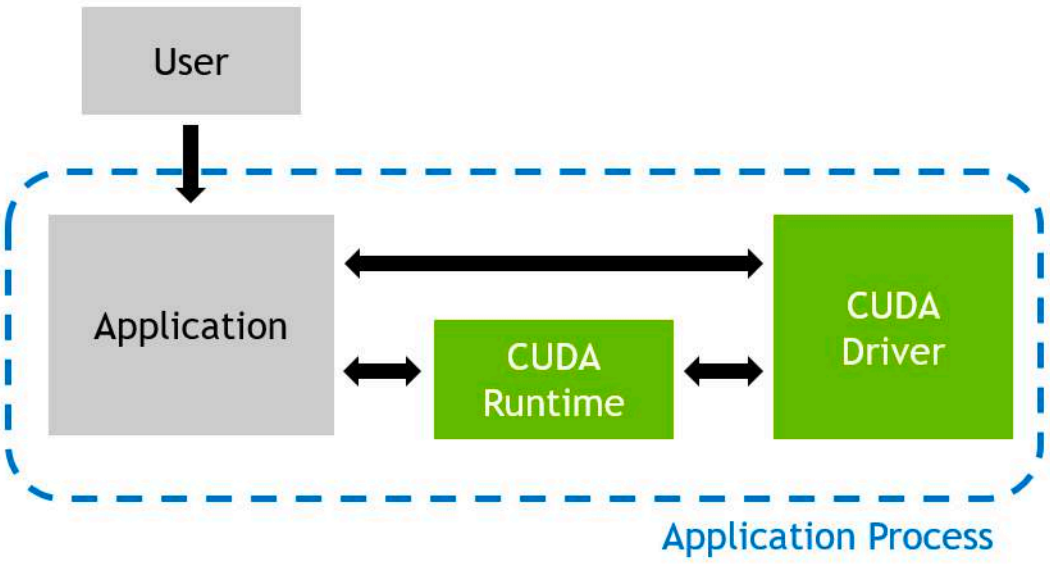
Complete Exascale Solution for ML/HPC

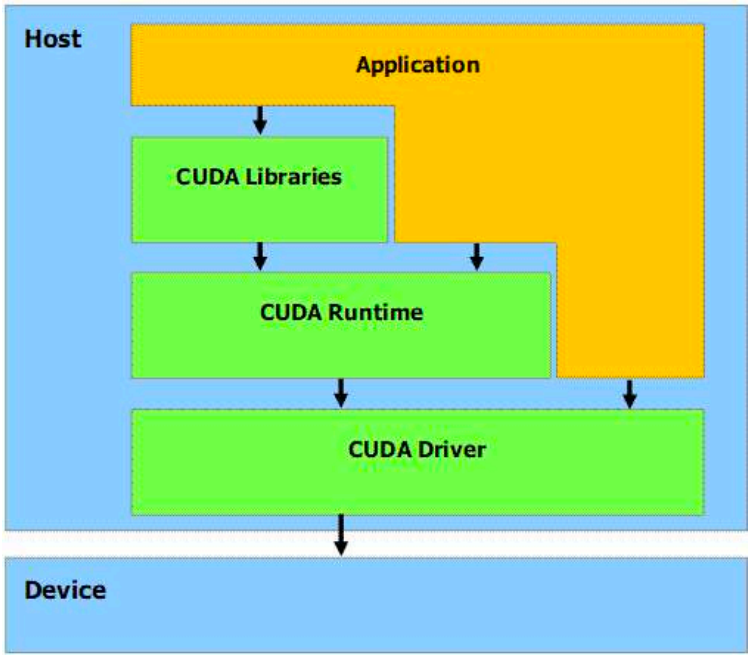
Applications	HPC Apps		ML Frameworks	
Cluster Deployment	Singularity	SLURM	Docker	Kubernetes
Tools	Debugger	Profiler, Tracer	System Valid.	System Mgmt.
Portability Frameworks	Kokkos	Magma	GridTools	ONNX
Math Libraries	RNG, FFT	Sparse	BLAS, Eigen	MIOpen
Scale-Out Comm. Libraries	OpenMPI	UCX	MPICH	RCCL
Programming Models	OpenMP	HIP	OpenCL	
Processors	CPU + GPU			

https://rocmdocs.amd.com/en/latest/

CUDA

- During regular execution, a CUDA application process will be launched by the user
- The application communicates directly with the CUDA user-mode driver, and potentially with the CUDA runtime library





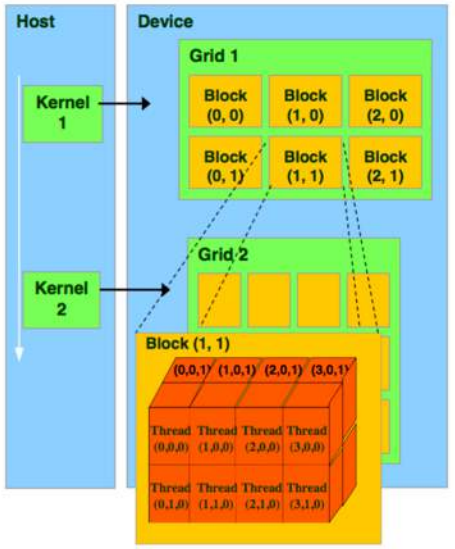
https://docs.nvidia.com/nsight-compute/ProfilingGuide/index.html

Detailed Kernel Launch[任务启动细节]

- S0: *application* creates user-mode queues (i.e., streams)
  - The queue is associated with a specific GPU
- S1: *application* places kernel dispatch packets into the queue
  - Done with user-level memory writes in ROCm (no kernel drivers)
  - Dependencies should be specified
- S2: *CPU* rings the doorbell to notify the CP of the GPU device
- S3: *CP* reads the packet, understands the kernel parameters
- S4: *CP* sends WGs to SPIs, which then launches WFs to CUs
- S5: when final WF is finished, *CP* sends a completion signal specified in the kernel dispatch packet
- S6: next, *CPU* receives an interrupt to pass the completion signal to runtime, which further completes the kernel in application code

Concurrency[并发]

- GPU is mainly known for its data-level parallelism[数据级并行]
  - Thousands of cores, with thousands of outstanding threads
  - Simultaneously computing the same function on lots of data elements
- Still need task-level parallelism[任务级并行]
  - GPU is underutilized by a single application process
  - Doing two or more completely different tasks in parallel
  - Similar to the task parallelism that is found in multithreaded CPU applications
- Techniques
  - Multi-process service (MPS)
  - Streams



http://www.mat.unimi.it/users/sansotte/cuda/CUDA_by_Example.pdf

GPU Context[上下文]

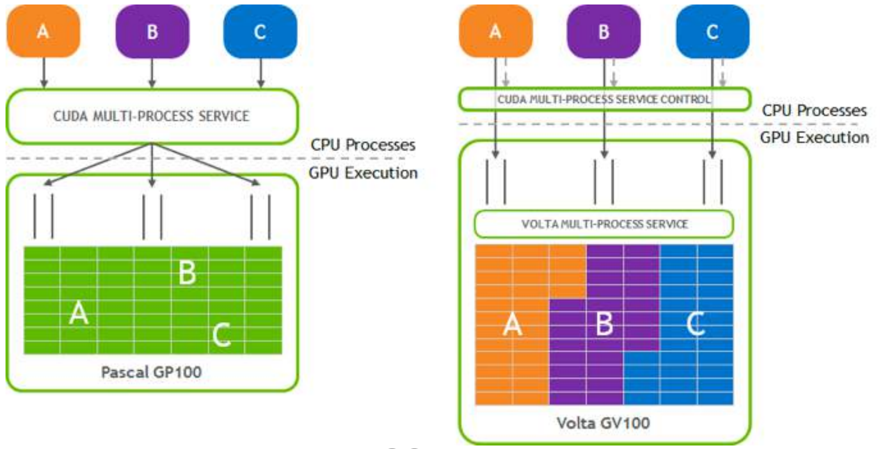
- A GPU program starts by creating a **context**
  - Either explicitly using the driver API or implicitly using the runtime API, for a specific GPU
- The **context** encapsulates all the hardware resources necessary for the program to be able to manage memory and launch work on that GPU

- Each process has a unique context[唯一]
  - Only a single context can be active on a device at a time
  - Multiple processes (e.g. MPI) on a single GPU could not operate concurrently

https://docs.nvidia.com/deploy/pdf/CUDA_Multi_Process_Service_Overview.pdf

MPS[多进程服务]

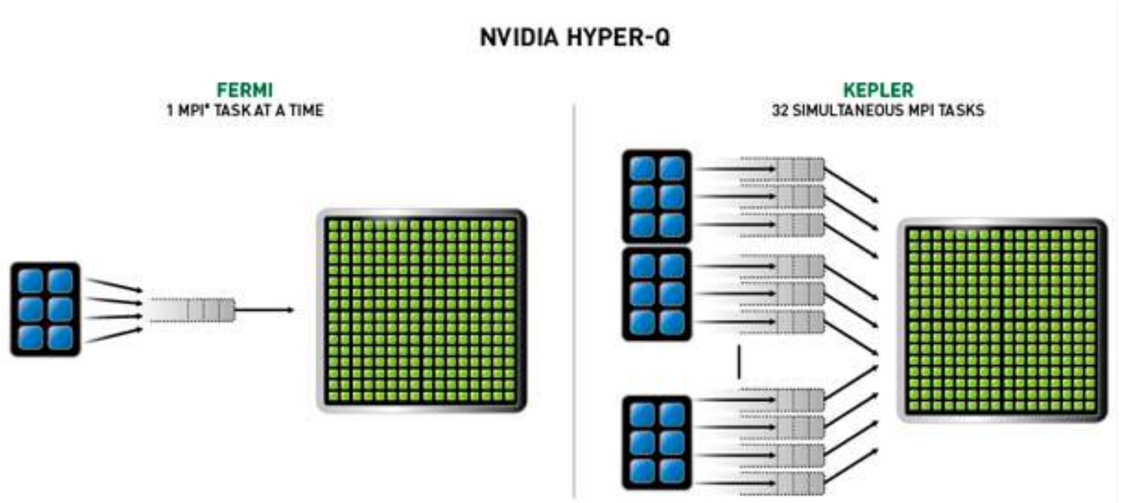
- **MPS**: multiple-process service, a software layer that sits between the driver and your application
  - Routes all CUDA calls through a single context
  - Multiple processes can execute concurrently
- Allows multiple processes to share a single GPU context, to utilize **Hyper-Q** capabilities
  - Hardware feature to construct multiple connections to GPU
  - Hyper-Q allows kernels to be processed concurrently on the same GPU


A
B
C
CUDA MULTI-PROCESS SERVICE
CPU Processes
GPU Execution
Pascal GP100
CUDA MULTI-PROCESS SERVICE CONTROL
VOLTA MULTI-PROCESS SERVICE
Volta GV100

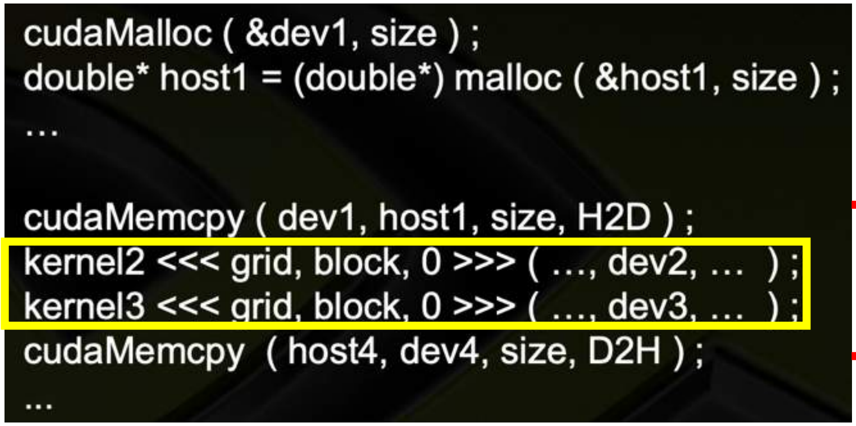
https://on-demand.gputechconf.com/gtc/2015/presentation/S5584-Priyanka-Sah.pdf

Hyper-Q[超队列]

- GPU's with **Hyper-Q** have a concurrent scheduler to schedule work from work queues belonging to a single CUDA context
- Work launched to the compute engine from work queues belonging to the same CUDA context can execute concurrently on the GPU

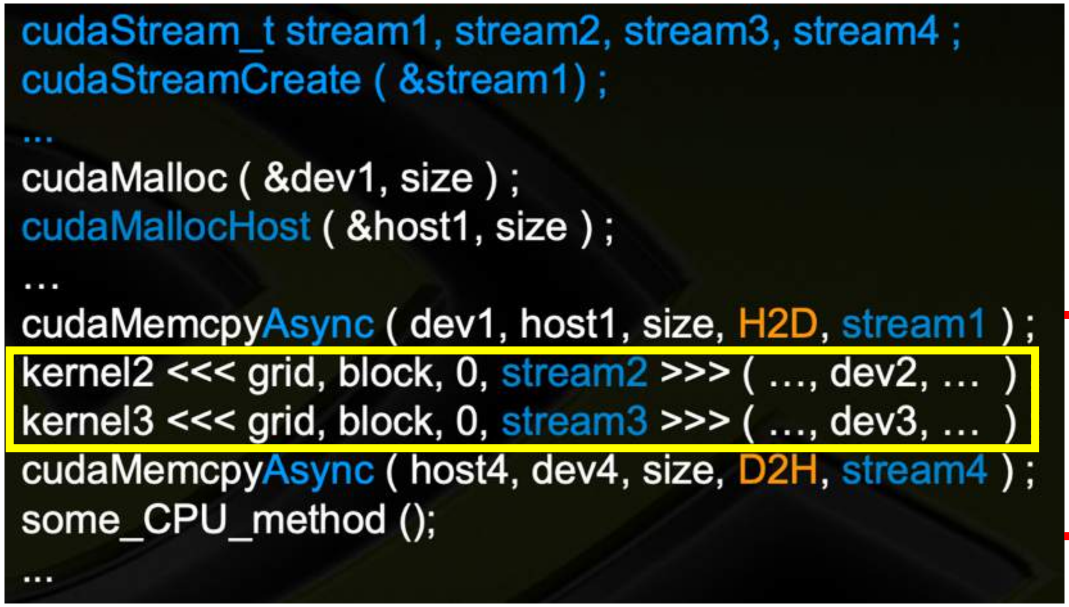


Code Example



```
cudaMalloc ( &dev1, size ) ;
double* host1 = (double*) malloc ( &host1, size ) ;
…

cudaMemcpy ( dev1, host1, size, H2D ) ;
kernel2 <<< grid, block, 0 >>> ( …, dev2, … ) ;
kernel3 <<< grid, block, 0 >>> ( …, dev3, … ) ;
cudaMemcpy  ( host4, dev4, size, D2H ) ;
...
```

Completely synchronous



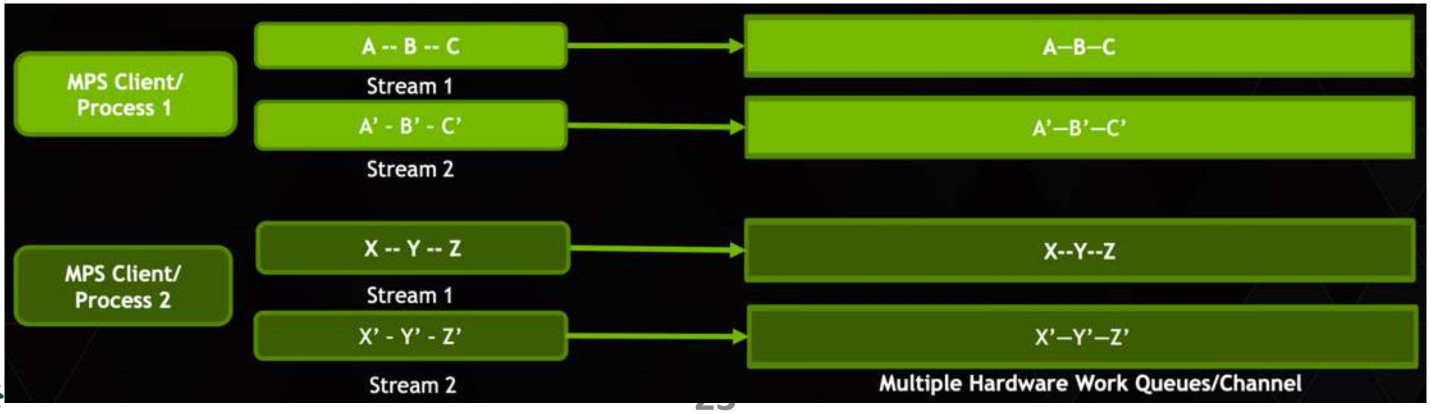
```
cudaStream_t stream1, stream2, stream3, stream4 ;
cudaStreamCreate ( &stream1) ;
...
cudaMalloc ( &dev1, size ) ;
cudaMallocHost ( &host1, size ) ;
…
cudaMemcpyAsync ( dev1, host1, size, H2D, stream1 ) ;
kernel2 <<< grid, block, 0, stream2 >>> ( …, dev2, … )
kernel3 <<< grid, block, 0, stream3 >>> ( …, dev3, … )
cudaMemcpyAsync ( host4, dev4, size, D2H, stream4 ) ;
some_CPU_method ();
...
```

Potentially overlapped

https://developer.download.nvidia.cn/CUDA/training/StreamsAndConcurrencyWebinar.pdf

Stream[流]

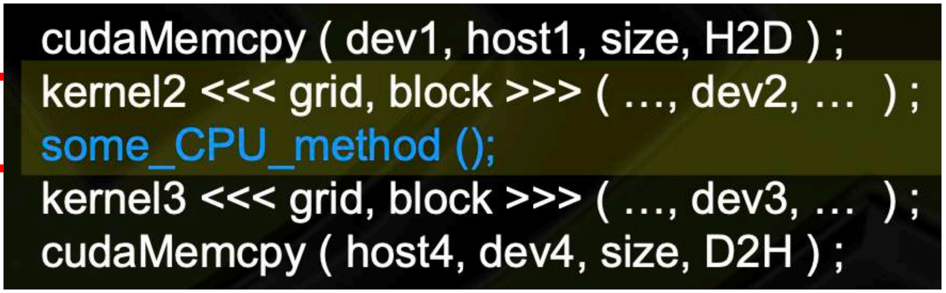
- All work on the GPU is launched either explicitly into a CUDA **stream**, or implicitly using a default stream
- A **stream** is a software abstraction that represents a sequence of commands to be executed in order
  - May be a mix of kernels, copies, and other commands
- CUDA streams are aliased onto one or more '**work queues**' on the GPU by the driver
  - Work queues are hardware resources that represent an in-order sequence of the subset of commands in a stream



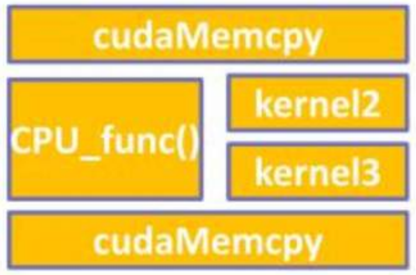
Synchronous/Asynchronous[同步/异步]

- All GPU API calls are either **synchronous** or **asynchronous** w.r.t the host
  - Synchronous: enqueue work and wait for completion
  - Asynchronous: enqueue work and return immediately
  - a.k.a., **blocking** vs. **non-blocking**[阻塞/非阻塞]
- The kernel launch function, *hipLaunchKernelGGL*, is **non-blocking** for the host
  - After sending instructions/data, the host continues immediately while the device executes the kernel
  - If you know the kernel will take some time, this is a good area to do some work on the host

Potentially overlap



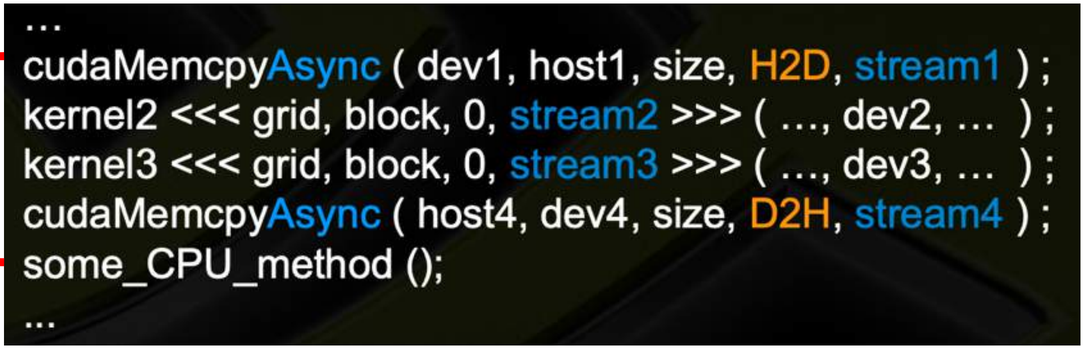
```
cudaMemcpy ( dev1, host1, size, H2D ) ;
kernel2 <<< grid, block >>> ( ..., dev2, ... ) ;
some_CPU_method ();
kernel3 <<< grid, block >>> ( ..., dev3, ... ) ;
cudaMemcpy ( host4, dev4, size, D2H ) ;
```



Synchronous/Asynchronous(cont.)

- However, *hipMemcpy* is **blocking**
  - The data pointed to in the arguments can be accessed/modified after the function returns
- The non-blocking version is *hipMemcpyAsync*
  - *hipMemcpyAsync(d_a, h_a, Nbytes, hipMemcpyHostToDevice, stream)*;
  - Like *hipLaunchKernelGGL*, this function takes an argument of type hipStream_t
  - It is not safe to access/modify the arguments of *hipMemcpyAsync* without some sort of synchronization.

Potentially overlap

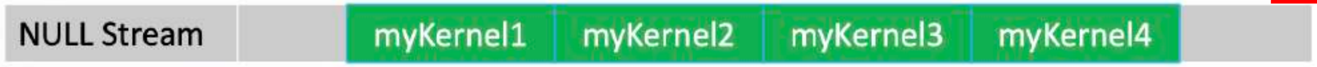


```
...
cudaMemcpyAsync ( dev1, host1, size, H2D, stream1 ) ;
kernel2 <<< grid, block, 0, stream2 >>> ( ..., dev2, ...  ) ;
kernel3 <<< grid, block, 0, stream3 >>> ( ..., dev3, ...  ) ;
cudaMemcpyAsync ( host4, dev4, size, D2H, stream4 ) ;
some_CPU_method ();
...
```

Streams[多流]

- A stream is a queue of device work
  - Host places work in the queue and continues on immediately
  - Device schedules work from streams when resources are free
- Operations are placed within a stream
  - e.g. Kernel launches, memory copies
- Default stream
  - Unless otherwise specified all calls are placed into a default stream (“Stream 0” or “NULL stream”)
    - Stream 0 has special sync rules: synchronous with all streams
    - Operations in stream 0 cannot overlap other streams

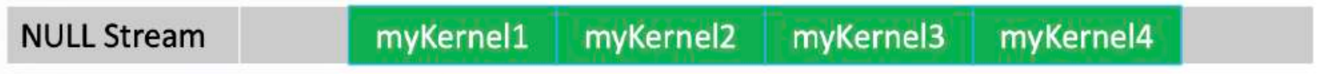
```
hipLaunchKernelGGL(myKernel1, dim3(1), dim3(256), 0, 0, 256, d_a1);
hipLaunchKernelGGL(myKernel2, dim3(1), dim3(256), 0, 0, 256, d_a2);
hipLaunchKernelGGL(myKernel3, dim3(1), dim3(256), 0, 0, 256, d_a3);
hipLaunchKernelGGL(myKernel4, dim3(1), dim3(256), 0, 0, 256, d_a4);
```



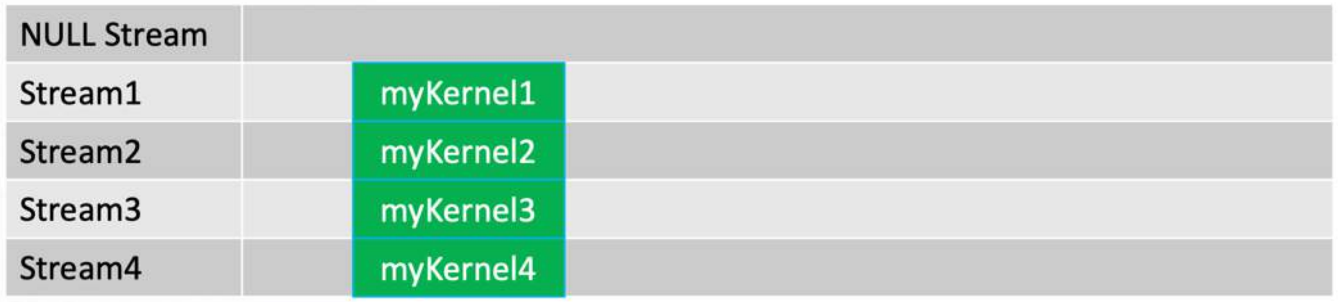
https://on-demand.gputechconf.com/gtc/2014/presentations/S4158-cuda-streams-best-practices-common-pitfalls.pdf

Streams (cont.)

- Operations within the same stream are ordered (FIFO) and cannot overlap
- Operations in different streams are unordered and can overlap



```
hipLaunchKernelGGL(myKernel1, dim3(1), dim3(256), 0, stream1, 256, d_a1);
hipLaunchKernelGGL(myKernel2, dim3(1), dim3(256), 0, stream2, 256, d_a2);
hipLaunchKernelGGL(myKernel3, dim3(1), dim3(256), 0, stream3, 256, d_a3);
hipLaunchKernelGGL(myKernel4, dim3(1), dim3(256), 0, stream4, 256, d_a4);
```



Synchronization[同步]

- How do we coordinate execution on device streams with host execution?
  - Need some synchronization points.
- *hipDeviceSynchronize()*; / *cudaDeviceSynchronize()*
  - Heavy-duty sync point
  - Blocks host until **all work** in **all device streams** has reported complete
- *hipStreamSynchronize(stream)*; / *cudaStreamSynchronize (stream)*
  - Blocks host until **all work** in **stream** has reported complete
- Can a stream synchronize with another stream?
  - For that we need ‘Events’

https://www.olcf.ornl.gov/wp-content/uploads/2019/09/AMD_GPU_HIP_training_20190906.pdf

Events[事件]

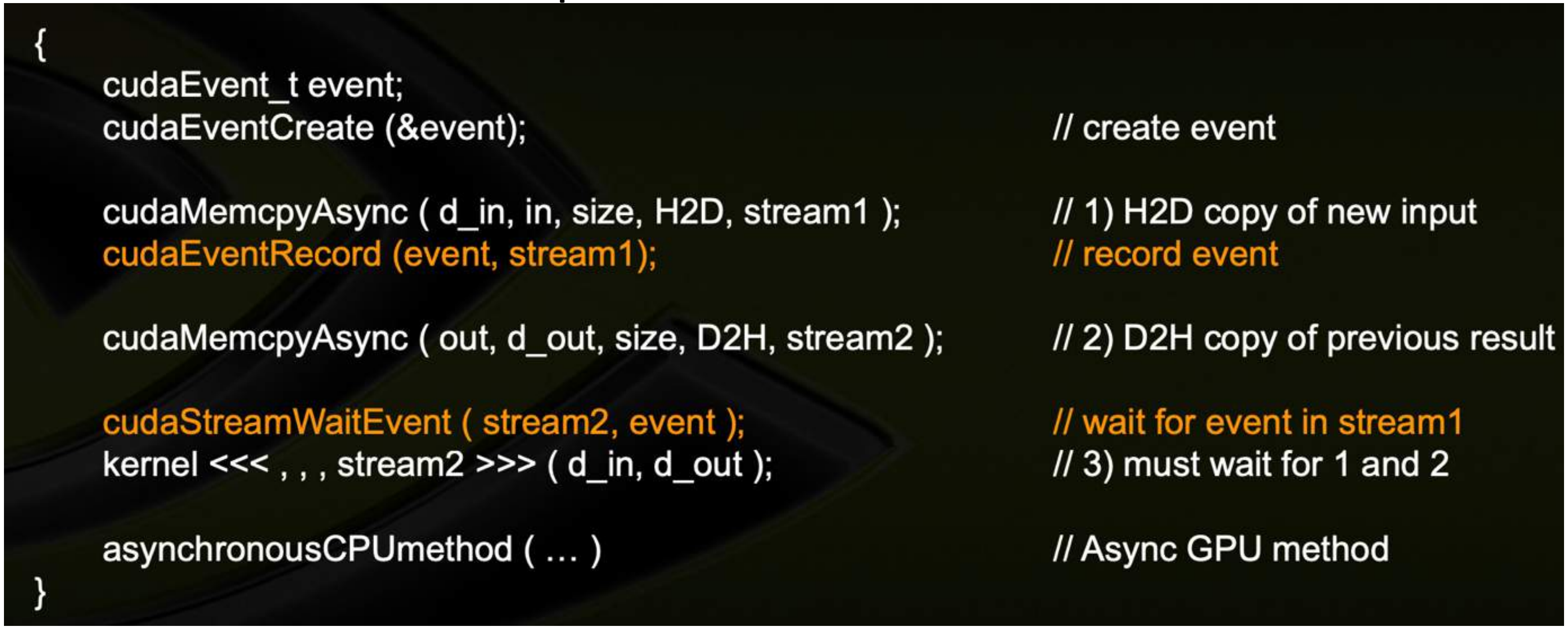
- Provide a mechanism to signal when operations have occurred in a stream
  - Useful for profiling and synchronization
  - Events have a boolean state: Occurred (default), Not Occurred
- A *hipEvent_t* object is created on a device via:
  - *hipEvent_t event;*
  - *hipEventCreate(&event);*
- We queue an event into a stream:
  - *hipEventRecord(event, stream)*;
  - The event records what work is currently enqueued in the stream
  - When the stream's execution reaches the event, the event is considered 'complete'
- At the end of the app, event objects should be destroyed:
  - *hipEventDestroy(event)*;

Events (cont.)

- *hipEventSynchronize(event)*;
  - Block host until event reports complete
  - Only a synchronization point with respect to the stream where event was enqueued
- *hipEventElapsedTime(&time, startEvent, endEvent)*;
  - Returns the time in ms between when two events, startEvent and endEvent, completed
  - Can be very useful for timing kernels/memcpys
- *hipStreamWaitEvent(stream, event)*;
  - Non-blocking for host
  - Instructs all future work submitted to stream to wait until event reports complete
  - Primary way we enforce an ‘ordering’ between tasks in separate streams

Example

- *cudaEventRecord(&event, stream)*
  - Enqueue an event into stream, whose state is set to occurred when reaching the front of the stream
- *cudaStreamWaitEvent(stream, event)*
  - The stream cannot proceed until the event occurs

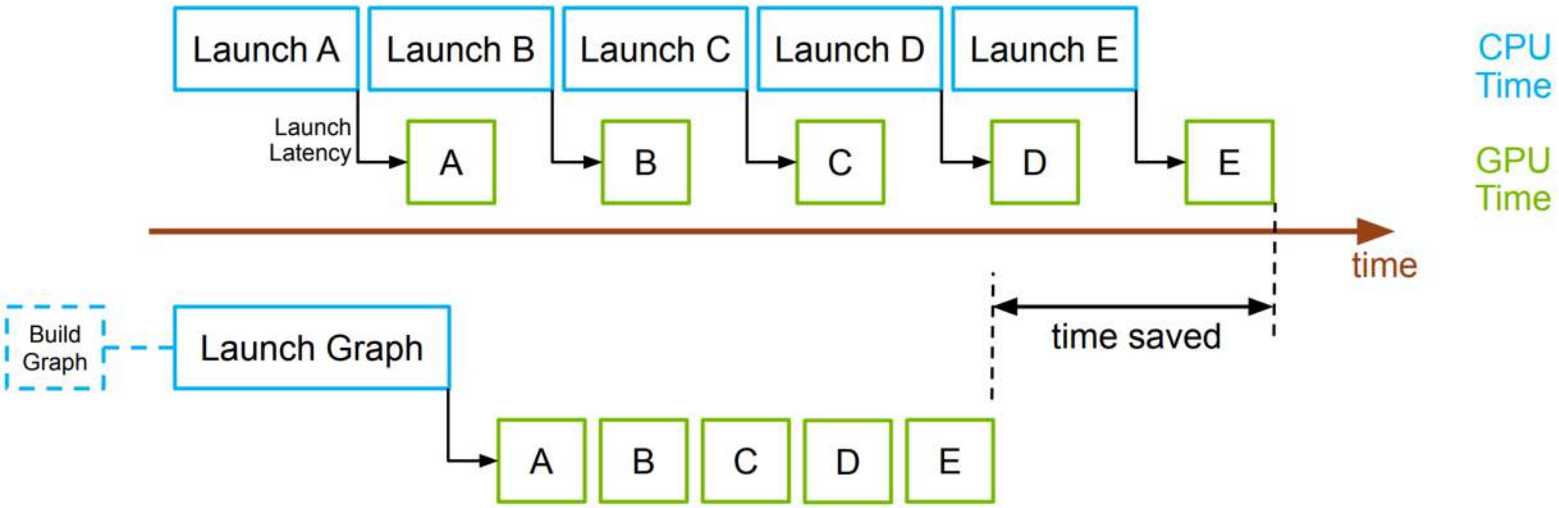


```
{
    cudaEvent_t event;
    cudaEventCreate (&event);                                  // create event

    cudaMemcpyAsync ( d_in, in, size, H2D, stream1 );          // 1) H2D copy of new input
    cudaEventRecord (event, stream1);                          // record event

    cudaMemcpyAsync ( out, d_out, size, D2H, stream2 );        // 2) D2H copy of previous result

    cudaStreamWaitEvent ( stream2, event );                    // wait for event in stream1
    kernel <<< , , , stream2 >>> ( d_in, d_out );              // 3) must wait for 1 and 2

    asynchronousCPUmethod ( … )                                // Async GPU method
}
```

https://developer.download.nvidia.cn/CUDA/training/StreamsAndConcurrencyWebinar.pdf

Task Graph[任务图]

- CPU launches each kernel to GPU
  - When kernel runtime is short, execution time is dominated by CPU launch cost
- CUDA graph launch submits all work at once, reducing CPU cost
  - A sequence of operations, connected by dependencies

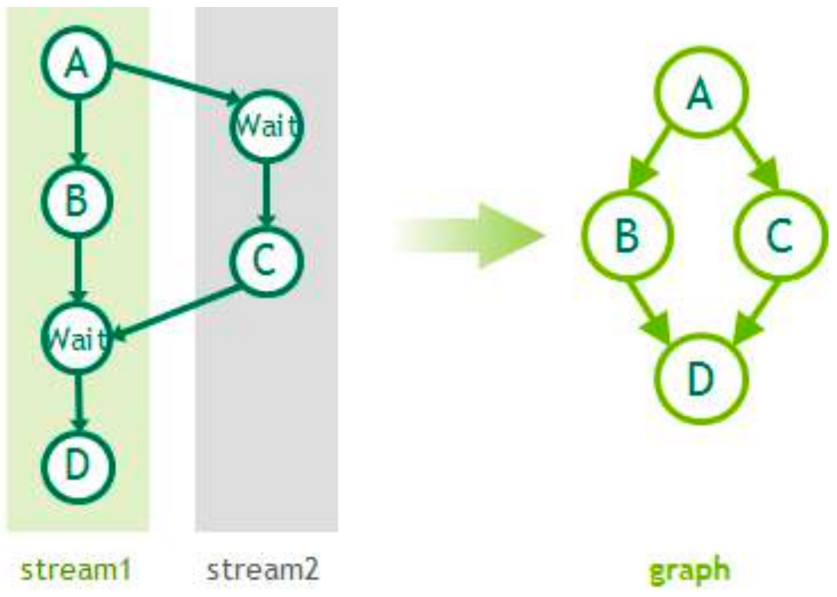


https://www.olcf.ornl.gov/wp-content/uploads/2021/10/013_CUDA_Graphs.pdf

Example

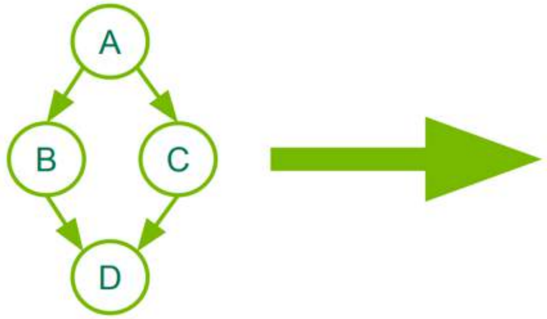
- Capture CUDA stream work into a graph[基于流构建]

```
// Start by initiating stream capture
cudaStreamBeginCapture(&stream1);

// Build stream work as usual
A<<< ..., stream1 >>>();
cudaEventRecord(e1, stream1);
B<<< ..., stream1 >>>();
cudaStreamWaitEvent(stream2, e1);
C<<< ..., stream2 >>>();
cudaEventRecord(e2, stream2);
cudaStreamWaitEvent(stream1, e2);
D<<< ..., stream1 >>>();

// Now convert the stream to a graph
cudaStreamEndCapture(stream1, &graph);
```



Example (cont.)

- Create graphs directly[直接构建]
  - Map graph-based workflows directly into CUDA

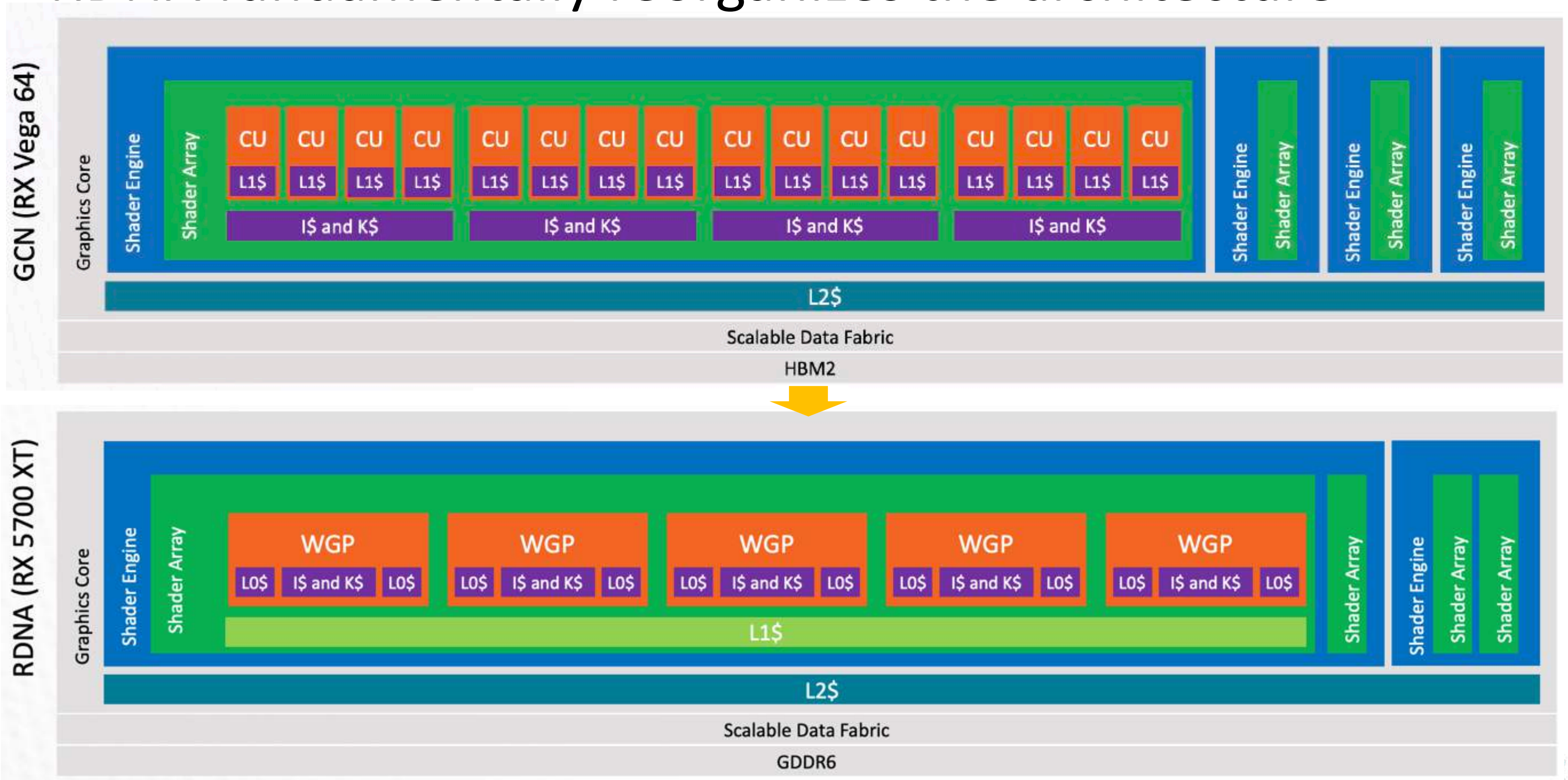


Graph from framework

```
// Define graph of work + dependencies
cudaGraphCreate(&graph);

cudaGraphAddNode(graph, kernel_a, {}, ...);
cudaGraphAddNode(graph, kernel_b, { kernel_a }, ...);
cudaGraphAddNode(graph, kernel_c, { kernel_a }, ...);
cudaGraphAddNode(graph, kernel_d, { kernel_b, kernel_c }, ...);

// Instantiate graph and apply optimizations
cudaGraphInstantiate(&instance, graph);

// Launch executable graph 100 times
for(int i=0; i<100; i++)
    cudaGraphLaunch(instance, stream);
```

GPU Memory Hierarchy[存储层级]

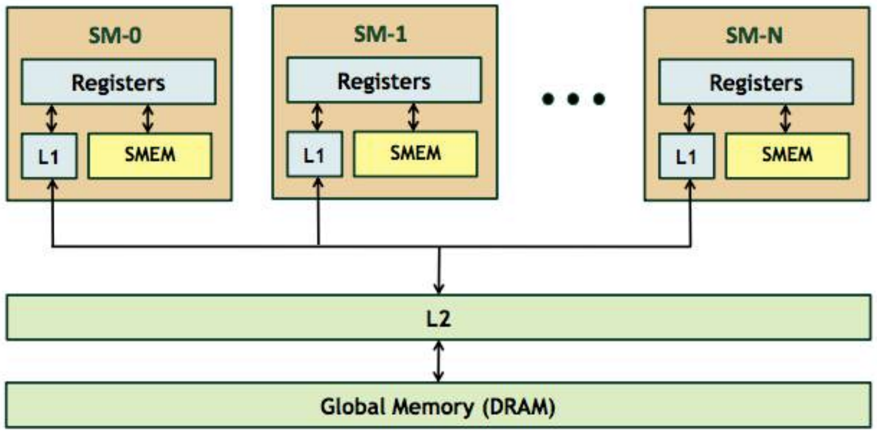
- CU internal memories: registers, caches, …
- Shared L2, off-chip HBM/GDDR
- RDNA fundamentally reorganizes the architecture

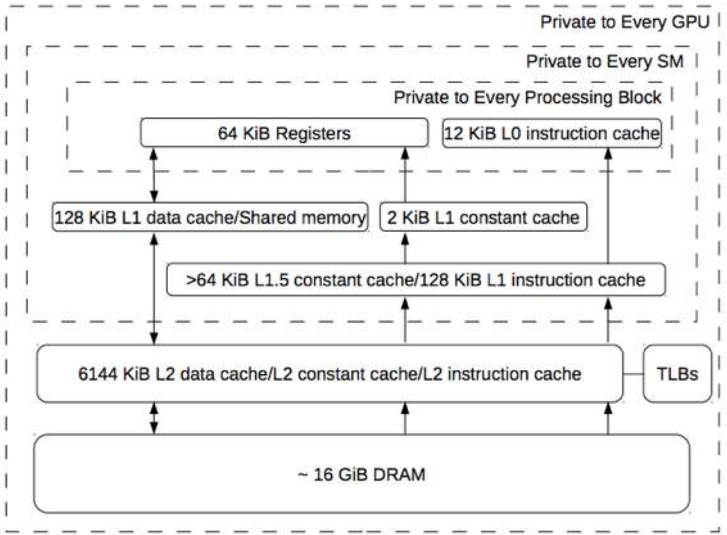


https://gpuopen.com/wp-content/uploads/2019/08/RDNA_Architecture_public.pdf

Memory Hierarchy

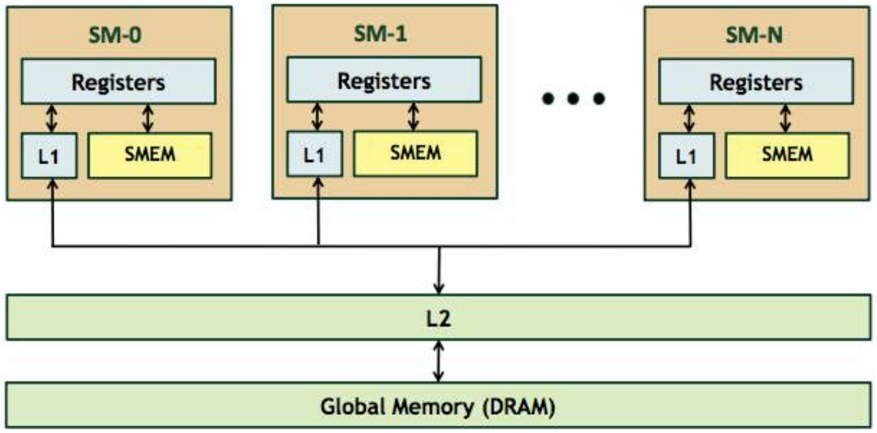
- **Register**: per-thread, deallocate when the thread done
- **Cache**: instruction, data, RO constant, RO texture
- **Global memory**: per-GPU, shared across kernels
- **Shared memory (SMEM)**: per-block, deallocate when the block done (and re-allocated to other blocks) LDS for AMD GPU
- **Constant memory (CMEM)**: part of device memory, use dedicated per-SM constant cache; shared across kernels




Private to Every GPU
Private to Every SM
Private to Every Processing Block
64 KiB Registers
12 KiB L0 instruction cache
128 KiB L1 data cache/Shared memory
2 KiB L1 constant cache
>64 KiB L1.5 constant cache/128 KiB L1 instruction cache
6144 KiB L2 data cache/L2 constant cache/L2 instruction cache
TLBs
~ 16 GiB DRAM

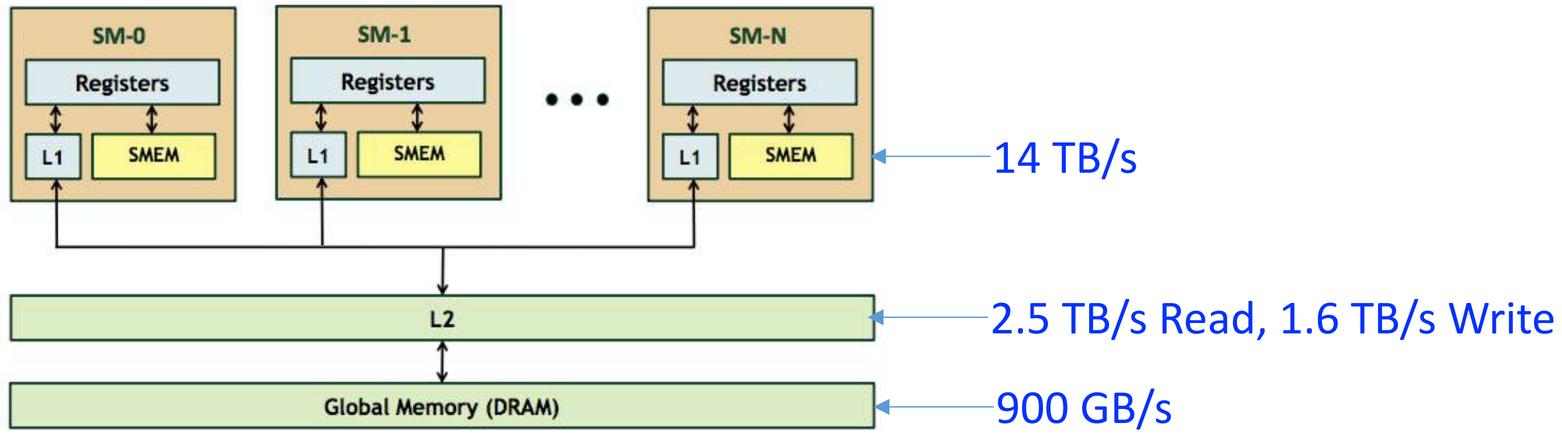
V100 Memory Hierarchy[存储层级]

- 80 SMs
  - Cores per SM: 64 INT32, 64 FP32, 32 FP64, 8 Tensor
  - Peak TFLOPS: 15.7 FP32, 7.8 FP64, 125 Tensor
  - Per SM: 64K 32-bit Register File, 128KB SMEM+L1
- 6MB L2 cache, 16GB 900GB/s HBM2
  - Shared by all SMs
  - For comparison: 20MB RF, 10MB SMEM+L1



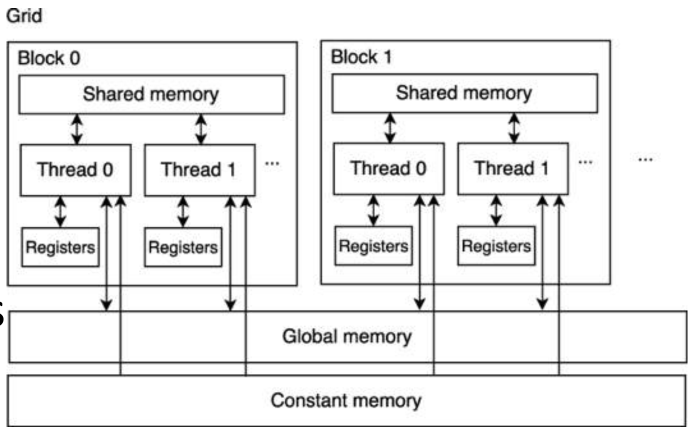
SMEM & CMEM

- SMEM benefits compared to DRAM:
  - 20-40x lower latency
  - ~15x higher bandwidth
  - Access granularity: 4B vs. 32B
- Constant memory (CMEM):
  - Total constant data size limited to 64KB
  - Throughput: 4B/clock per SM
  - Can be used directly in arithmetic insts (saving regs)



Resource Limits[资源限制]

- Threads[线程]
  - Max per SM: 32 TBs, 64 Warps (i.e., 2048 threads)
    - Up to 1024 threads/TB
    - TBs should be of at least 2 warps
- Registers[寄存器]
  - Max: 64K regs/TB, 255 regs/thread
    - Per SM: total 64K regs
    - If exceeding 255 regs, then spilling happens
- Memory[存储]
  - Max 96KB SMEM per SM (default 48KB)
- 100% occupancy[若满载]
  - 2048 threads/SM, 64K regs/SM → 32 regs/thread (128B)
  - 2048 threads/SM, 96KB smem/SM → 32B/thread



Memory Space Specifiers[存储空间指定]

- Variable memory space specifiers denote the memory location on the device of a variable
- **__device__**: declares a variable that resides on the device, by default
  - Resides in global memory space
  - Has the lifetime of the CUDA context in which it is created
  - Is accessible from all the threads within the grid and from the host through the runtime library
- **__constant__**: declares a variable that resides in constant memory space
  - Optionally used together with __device__
- **__shared__**: declares a variable that resides in shared memory space
  - Has the lifetime of the block,
  - Is only accessible from all the threads within the block

https://docs.nvidia.com/cuda/cuda-c-programming-guide/index.html#variable-memory-space-specifiers

Memory Space Specifiers (cont.)

- **__managed__**: declares a variable that can be referenced from both device and host code
  - optionally used together with __device__
  - Has the lifetime of an application
- An automatic variable declared in device code without any of the __device__, __shared__ and __constant__ specifiers generally resides in a register
  - However in some cases the compiler might choose to place it in local memory, which can hurt performance

Variable declaration	Memory	Scope	Lifetime
__device__ int globalVar;	global	grid	application
__shared__ int sharedVar;	shared	block	block
__constant__ int constantVar;	constant	grid	application
int localVar;	register	thread	thread
int localArray[10];	local	thread	thread

Local Memory['本地'内存]

- Name refers to memory where registers and other thread-data is spilled
  - Usually when one runs out of SM resources
  - "Local" because each thread has its own private area
- Use **case 1**: register spilling[寄存器溢出]
  - Fermi hardware limit is 63 registers per thread (255 now)
  - Programmer can specify lower registers/thread limits:
    - To increase occupancy (number of concurrently running threads)
    - -maxrregcount option to nvcc, __launch_bounds__() qualifier in the code
  - LMEM is used if the source code exceeds register limit
- Use **case 2**: arrays declared inside kernels, if compiler can't resolve indexing[核函数内数组]
  - Registers aren't indexable, so have to be placed in LMEM

https://developer.download.nvidia.com/CUDA/training/register_spilling.pdf

Local Memory (cont.)

- LMEM is not really a memory
  - Bytes are actually stored in global memory
  - Differences from global memory:
    - Addressing is resolved by the compiler
    - Stores are cached in L1
- LMEM could hurt performance in two ways:
  - Increased memory traffic
  - Increased instruction count
- Spilling/LMEM usage isn't always bad
  - LMEM bytes can get contained within L1
    - Avoids memory traffic increase
  - Additional instructions don't matter much if code is not instruction-throughput limited

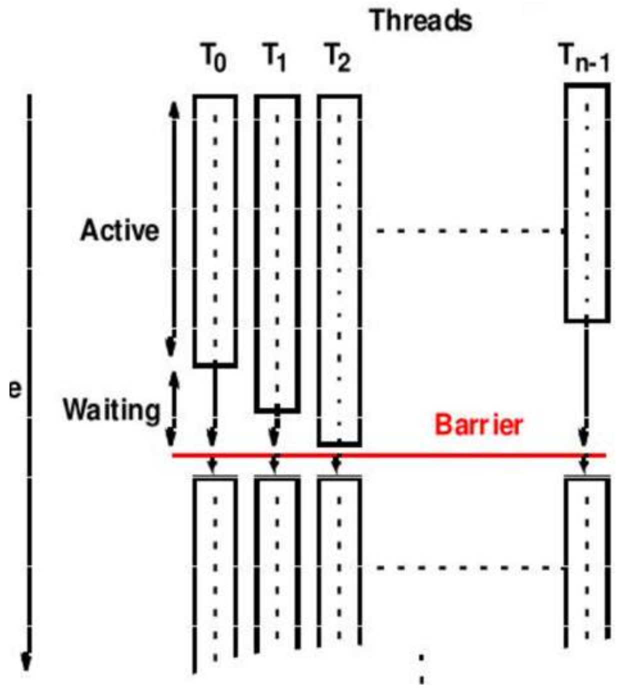
https://developer.download.nvidia.com/CUDA/training/register_spilling.pdf

Shared Memory[“共享”存储]

- A per-block, software managed cache or scratchpad
  - Programmer can modify variable declarations with __shared__ to make this variable resident in shared memory
  - Compiler creates a copy of the variable for each block
    - Every thread in that block shares the memory, but threads cannot see or modify the copy of this variable that is seen within other blocks
    - This provides an excellent means by which threads within a block can communicate and collaborate on computations
- CUDA L1 cache and SMEM are unified
  - cudaDeviceSetCacheConfig(enum cudaFuncCache)
- A mechanism is needed to **synchronize** between threads
  - *Thread A* writes a value to shared memory and we want *thread B* to do something with this value
  - We can’t have *thread B* start its work until we know the write from *thread A* is complete

Shared Memory (cont.)

- One can specify synchronization points in the kernel by calling __syncthreads()
- __syncthreads() acts as a barrier at which all threads in the block must wait before any is allowed to proceed
  - Guarantees that every thread in the block has completed instructions prior to the __syncthreads() before the hardware will execute the next inst on any thread
  - When the first thread executes the first instruction after __syncthreads(), every other thread in the block has also finished executing up to the __syncthreads()



Time

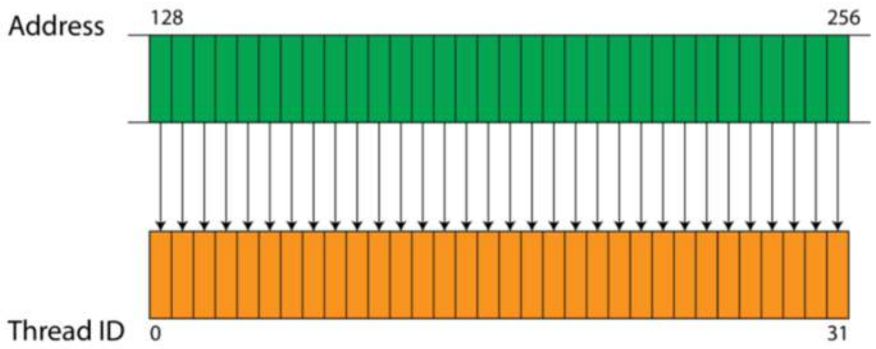
http://www.mat.unimi.it/users/sansotte/cuda/CUDA_by_Example.pdf

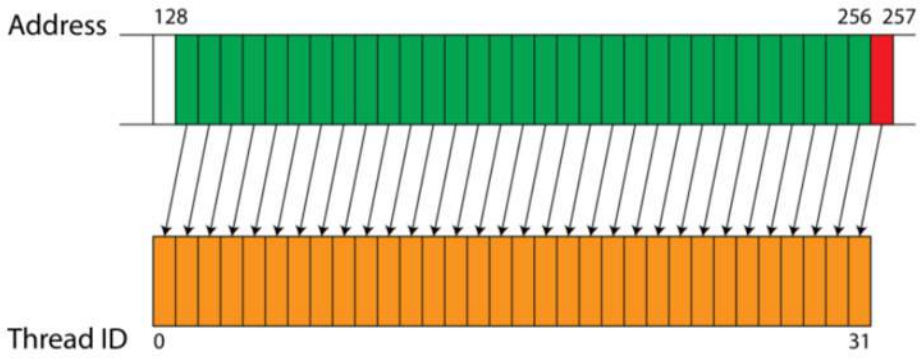
Example

```
__global__ void reverse(double *d_a) {
  __shared__ double s_a[256]; //array of doubles, shared in this block

  int tid = threadIdx.x;
  s_a[tid] = d_a[tid];    //each thread fills one entry

  //all wavefronts must reach this point before any wavefront is allowed to continue.
                        //something is missing here…
__syncthreads();

  d_a[tid] = s_a[255-tid]; //write out array in reverse order
}

int main() {
  …
  hipLaunchKernelGGL(reverse, dim3(1), dim3(256), 0, 0, d_a); //Launch kernel
  …
}
```

Address Coalescing[地址合并]

- Threads in a block are computed a warp at a time (32 threads)
- Global data is read or written in as few transactions as possible by combining memory access requests into a single transaction
  - This is referred to the device coalescing mem stores and reads
- Every successive 128 bytes can be accessed by a warp (or 32 single precision words)
- Not in successive 128 bytes; more data to read



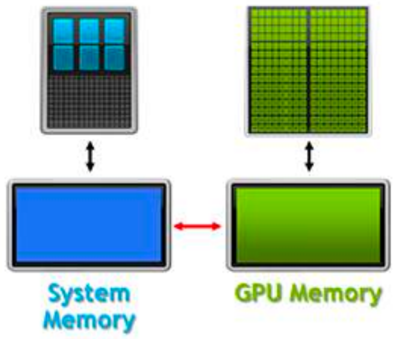


https://www.ce.jhu.edu/dalrymple/classes/602/Class13.pdf

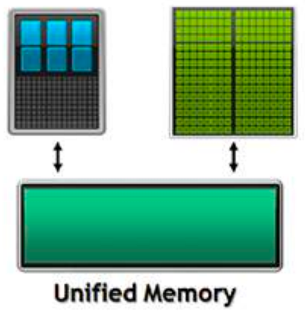
Unified Memory[统一内存]

- Classical model[经典模型]
  - Allocate memory on host
  - Allocate memory on device
  - Copy data from host to device Operate on the GPU data
  - Copy data back to host
- Unified memory model[统一模型]
  - Allocate memory
  - Operate on data on GPU
- Unified Memory is a single memory address space accessible from any processor in a system
  - cudaMalloc() → cudaMallocManaged()
  - on-demand page migration

Traditional Developer View

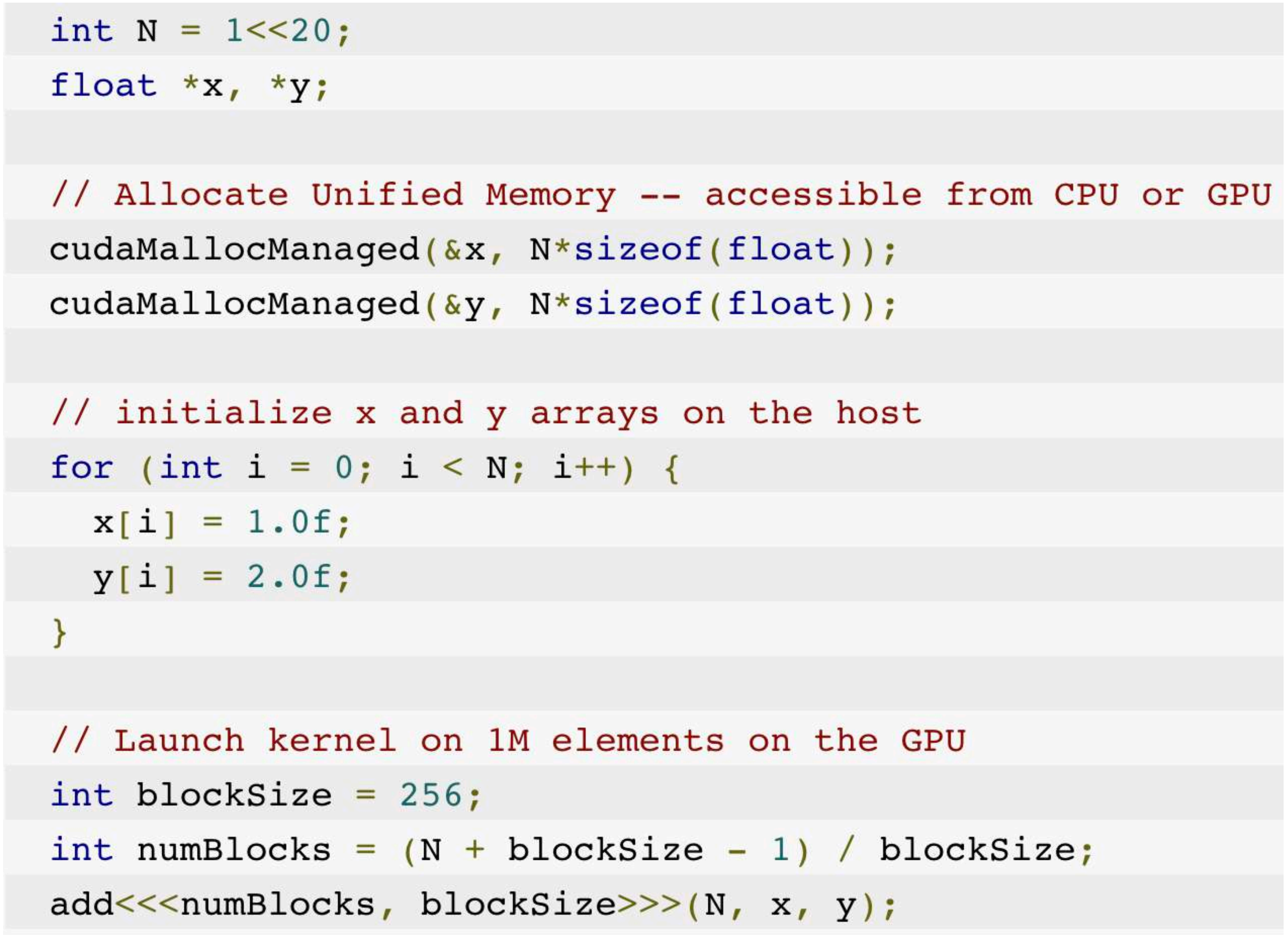


Developer View With Unified Memory



https://developer.nvidia.com/blog/unified-memory-cuda-beginners/

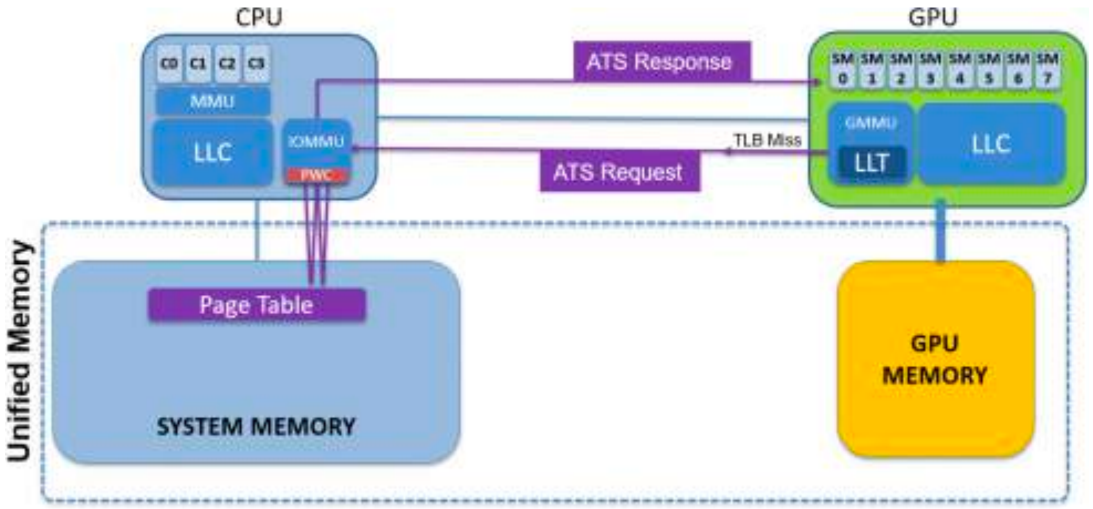
Example

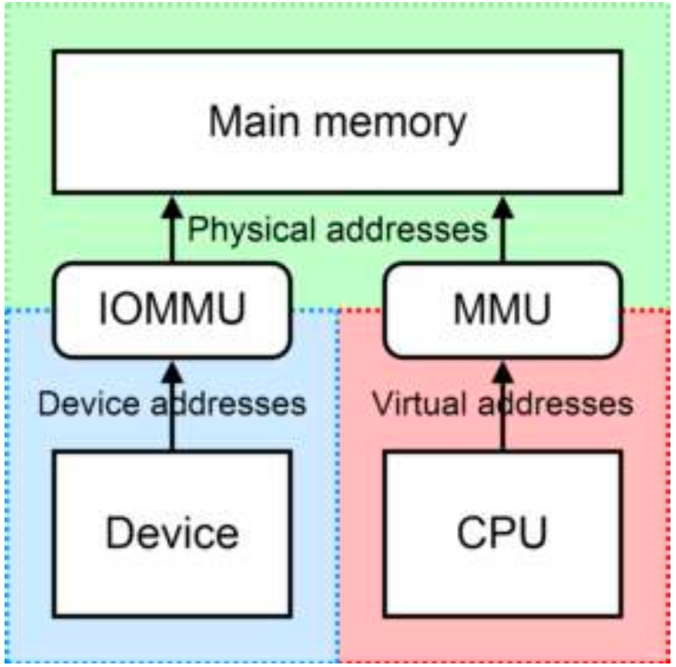


```
int N = 1<<20;
float *x, *y;

// Allocate Unified Memory -- accessible from CPU or GPU
cudaMallocManaged(&x, N*sizeof(float));
cudaMallocManaged(&y, N*sizeof(float));

// initialize x and y arrays on the host
for (int i = 0; i < N; i++) {
  x[i] = 1.0f;
  y[i] = 2.0f;
}

// Launch kernel on 1M elements on the GPU
int blockSize = 256;
int numBlocks = (N + blockSize - 1) / blockSize;
add<<<numBlocks, blockSize>>>(N, x, y);
```

Address Translation[地址转换]

- GMMU: GPU memory management unit
  - Last level TLB (LLT)
- IOMMU: maps device-visible virtual addresses to physical addresses
  - Page walk caches (PWC)



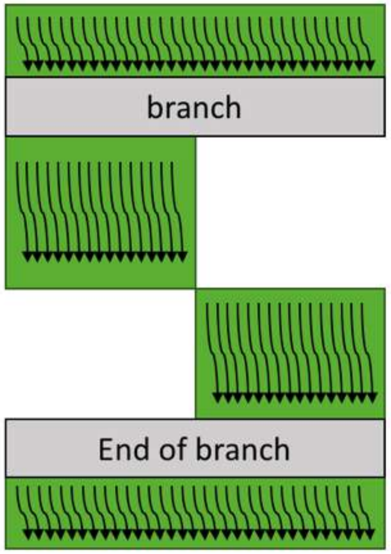


Divergence[分支]

- Within a block of threads, the threads are executes in groups of 32 called a warp
  - All threads in a warp do the same thing at the same time
- What happens if different threads in a warp need to do different things?
  - A logical predicate and two predicated instructions → serialized
- Branch divergence is a major cause for performance degr adation in GPGPUs

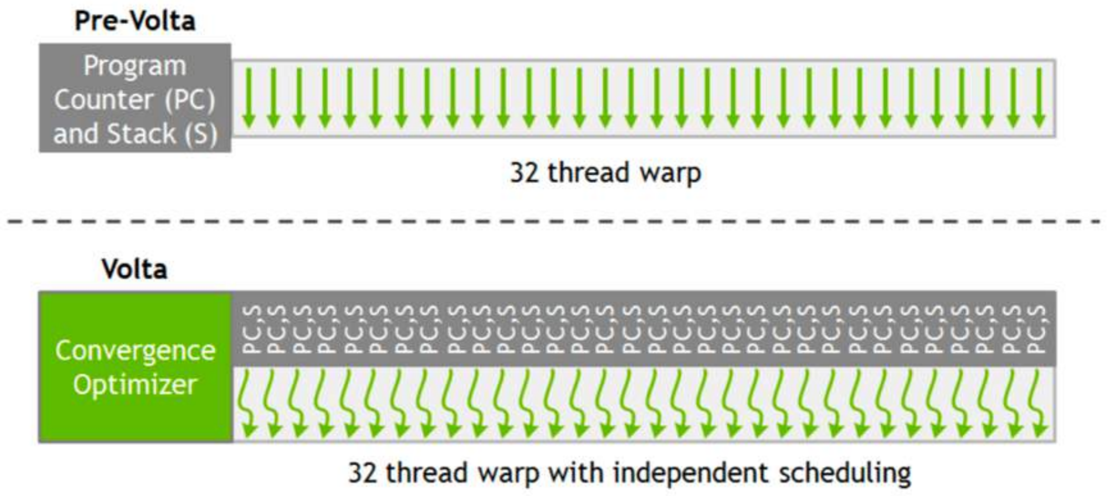
```
...
if ( threadIdx.x < 16 )
{
    ... A ...
}
else
{
    ... B ...
}
...
```

```
p = (threadIdx.x < 16);
if (p) ... A ...
if (!p) ... B ...
```



Divergence (cont.)

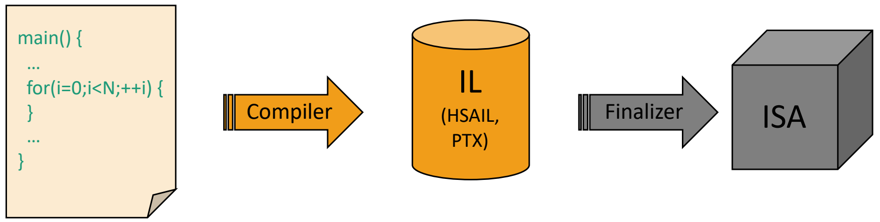
- Pre-Volta GPUs use a single PC shared amongst all 32 threads of a warp, combined with an active mask that specifies which threads of the warp are active at any given time
  - Leaves threads that are not executing a branch inactive
- Since Volta, each thread features its own PC, which allows threads of the same warp to execute different branches of a divergent section simultaneously

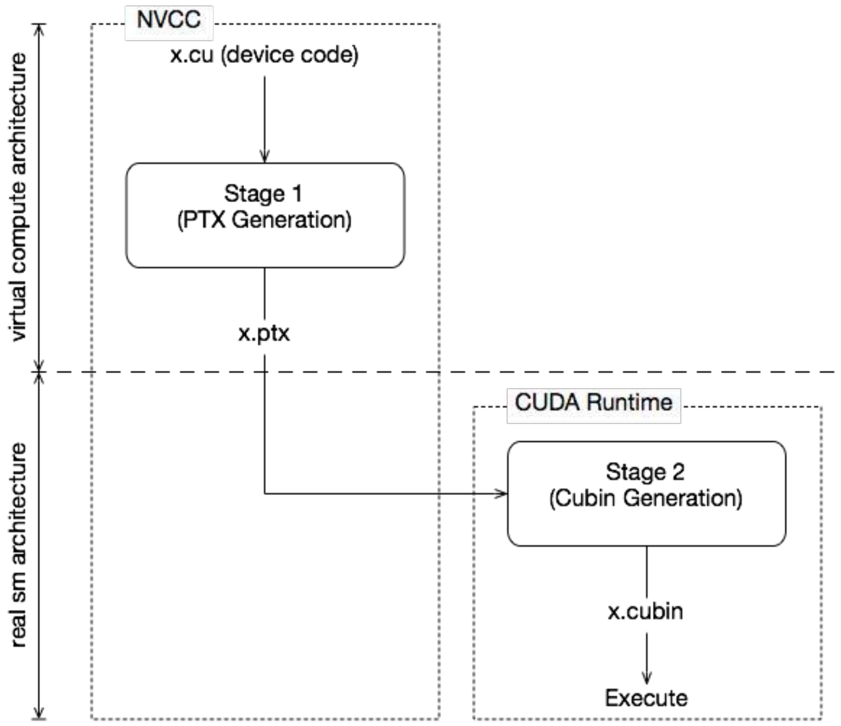

Pre-Volta
Program Counter (PC) and Stack (S)
32 thread warp
Volta
Convergence Optimizer
PC,S
32 thread warp with independent scheduling

https://www.icl.utk.edu/files/publications/2018/icl-utk-1080-2018.pdf

Two-phase Execution[两段式]

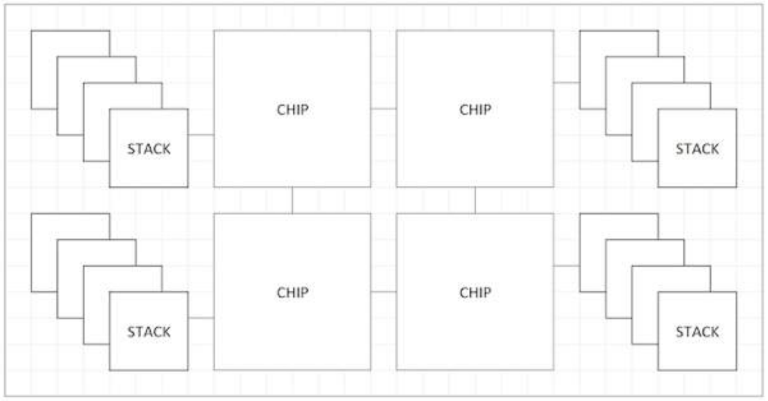
- Compilation workflow
  - Source code → virtual instruction (PTX or HSAIL)
  - Virtual inst → real inst (SASS or GCN)
- **.cu**: CUDA source file, containing host code and device functions
- **.ptx**: PTX intermediate assembly file
- **.cubin**: CUDA device code binary file (CUBIN) for a single GPU architecture

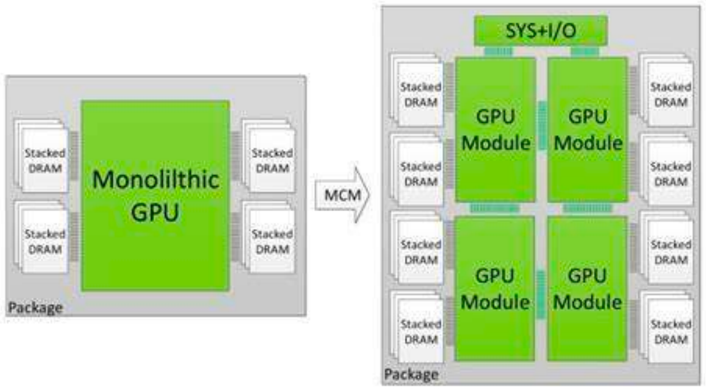




Multi-chip Module

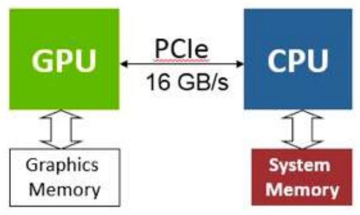
- Aggregating multiple GPU modules within a single package, as opposed to a single monolithic die.
- AMD: Chiplet GPUs
  - MI200: 220 compute units, 14K streaming cores
  - MI100: 120 compute units, 7680 streaming cores
- Nvidia: Multi-Chip-Module (MCM) GPUs
  - Hopper (Ampere -> Lovelace): 300+ SMs, 40K+ CUDA cores
  - A100: 128 SMs, 8192 CUDA cores



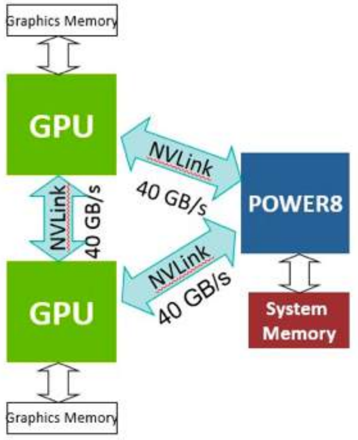


High-speed Links[高速连接]

- GPUs are of high compute capability, being bottlenecked on data movement
- High-speed interconnect to achieve significantly higher data movement
  - Nvidia: NVLink
  - AMD: Infinity Fabric
  - Intel: Compute eXpress Link (CXL)



CPU-GPU Systems Connected via PCI-e



NVLink Enables Fast Unified Memory Access between CPU & GPU Memories