# GPU Architecture

#### Multi-threaded Architecture

## Learning Objectives

- 1. Explain the difference between multithreading and context switching
- 2. Describe resource requirements for GPU multithreading

#### **GPU** Architecture

- 1. Many multiprocessors
- 2. Multithreading
- 3. Warp/wave front execution
- 4. Shared memory
- 5. Hardware caches

## Multithreading

- 1. In an in-order processor, following instructions must stall on a cache miss
  - In an out-of-order processor, instructions only have to stall if there's a dependency
- 2. When multithreading, the processor can simply switch to another thread when one is stalled

# Benefits of Multithreading

- 1. Hide processor stall time:
  - Cache misses
  - Branch instructions
  - Long latency operations (ALU operations)
- 2. GPUs use multithreading to hide latency
  - Out of order processors (OOO) use cache and ILP to hide latency
- 3. Longer memory latency requires a greater number of threads to hide latency

## Front-end Extension for Multithreading

- 1. Multiple PC registers for warps (one PC for each warp)
- 2. One static instruciton for one warp
  - SPMD programming model
- 3. Individual registers for each thread
  - Minimizes context switch overhead
  - Significant resource

#### **CPU Context Switching**

- 1. CPU context switch: Store PC, architecture registers in stack/memory
- 2. High overhead of CPU context switching

#### Hardware Support for Multithreading

- 1. Front-end needs to have multiple PCs
  - One PC for each warp since all threads in a warp share the same PC
  - Later GPUs have other advanced features
- 2. Large register file
  - Each thread needs "K" number of architecture registers
  - Total register file size requirement = K \* number of threads
  - "K" varies by applications
- 3. Remember occupancy calculation?

- Each SM can execute Y number of threads, Z number of registers, etc.
- Y is related to # of PC registers
- Z is related to K

## Revisit Previous Occupancy Calculation Example

- 1. Hardware example: SM can execute 256 threads, 64K registers, 32 KB shared memory, warp size is 32
  - How many PCs are needed in one SM?
    - -256 / 32 = 8 PCs
  - If a program has 10 instructions, how many times does one SM fetch an instruction?
    - -10\*8=80

## **Summary**

- 1. GPU supports multithreading for performance enhancement
- 2. GPU hardware manages resources by warp for scalability

#### **Bank Conflicts**

## Learning Objectives

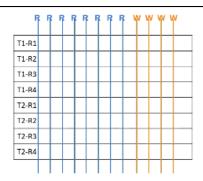
- 1. Explain SIMT behavior of register file accesses and shared memory accesses
- 2. Describe techniques to enhance bandwidth in register and shared memory accesses

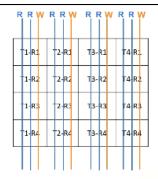
## CUDA Block/Threads/Warps

- 1. Multiple blocks can be running on one multiprocessor
- 2. Each block has multiple threads
- 3. A group of threads are executed as a warp
- 4. Registers are per thread
- 5. Execution width \* 3 (2 source registers, 1 destination register) total register accesses

## Port vs Bank

- 1. Port: Hadware interface for data access
  - Each thread requires 2 read and 1 write ports and execution width is 4
    - 8 read ports and 4 write ports
- 2. Bank: A partition (group) of the register file
  - Instead of placing 2 read and 1 write port per thread, place 2 read and 1 write per register element
  - Multiple banks can be accessed simultaneously
  - More ports mean more hardware wiring and resource usage





8 read ports and 4 write ports per each register element

2 read ports and 1 write port per each register element

4 bank version



No bank version

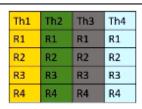
Port vs Bank

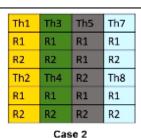
#### **Bank Conflict**

- 1. Scenario 1: Read R1 from T1, T2, T3, T4
  - Each thread on different banks, no conflict
- 2. Scenario 2: Read R1, R2, R3, R4 from T1
  - Bank conflict!
    - Can't read 8 values from any location, only 2 values from each bank
  - Takes multiple cycles

#### Variable Number of Registers per Thread

- 1. CUDA programming will get benefits from different register counts per thread
- 2. Instruction R3 = R1 + R2
  - Case 1: 4 registers per 1 thread
    - Reading registers would not cause a bank conflict
  - Case 2: 2 registers per 1 thread
    - Read R1, R2 from multiple threads would cause a bank conflict!
    - Remember: GPU executes a group of threads (warp), so multiple threads are reading the same registers





Different colors different banks

Case 1

Bank Conflict

#### Solutions to Overcome Register Bank Conflict

- 1. Compiler-driven solution for optimizing code layout
  - Register ID is known at static time
- 2. Note: Not all register bank conflicts can be avoided
- 3. Complexity beyond a 5-stage pipline:

- Register file access takes more than 1 cycle
- Source register values are buffered

## Static vs Dynamic

- 1. In this course, static often means before running code. The property is not dependent on input of the program. Dynamic means that the property is dependent on input of the program
  - e.g., static/dynamic number of instructions
    - LOOP: ADD R1, R1, 1
    - BREQ R1, 10, LOOP
- 2. Let's say that a loop iterates 10 times. Static number of instructions is 2, dynamic number of instructions is 20
  - Static time analysis = compile time analysis

# Scoreboarding

- 1. Widely used in CPU to enable out of order execution
- 2. Dynamic instruction scheduling
- 3. GPUs: check when all source operands within a warp are ready; the warp is sent to execution units
  - Choose which one to send to the execution unit among multiple warps
    - e.g., oldest first

## Reading Register Values

- 1. Reading register files might take a few cycles
- 2. Ready register values are stored at a buffer

#### **Shared Memory Bank Conflicts**

- 1. Shared memory is an on-chip storage
  - Scratch pad memory
  - Also composed with banks
- 2. Let's assume the following shared memory:
  - 4 banks; number is memory address
    - shared float shared input[index1];
    - index1 = threadIdx.x \* 4;
  - Then thread1:mem[4], thread2:mem[8], thread3:mem[12], ...
    - All threads will generate bank conflicts
  - Solution: Change the software structures (covered more in later lectures)

#### Summary

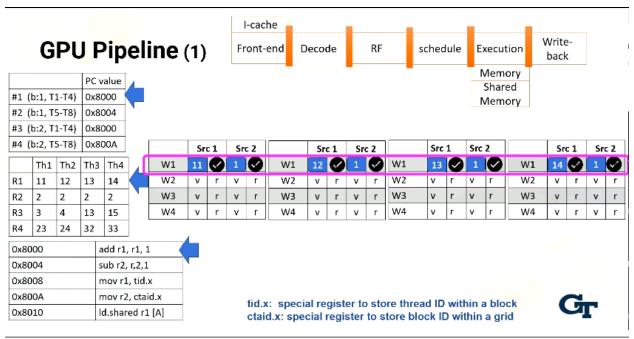
- 1. Learned the benefits of banks in register and shared memory
- 2. The reasons of bank conflicts in register files and shared memory

## GPU Architecture Pipeline

## Learning Objectives

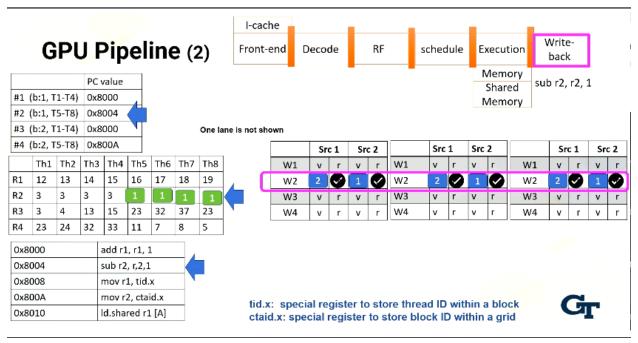
- 1. Describe GPU pipeline behavior with multithreading and register file access
- 2. Explain how mask bits are used

#### GPU Pipeline 1



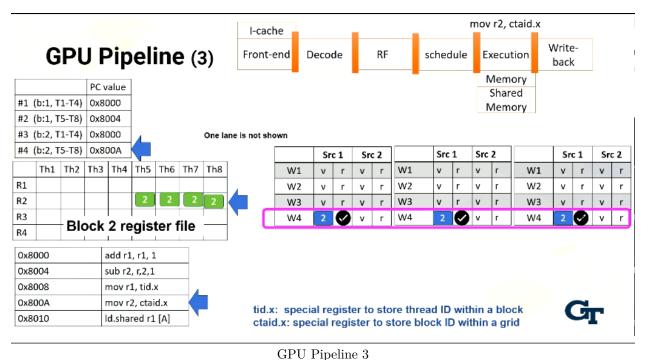
GPU Pipeline 1

## GPU Pipeline 2



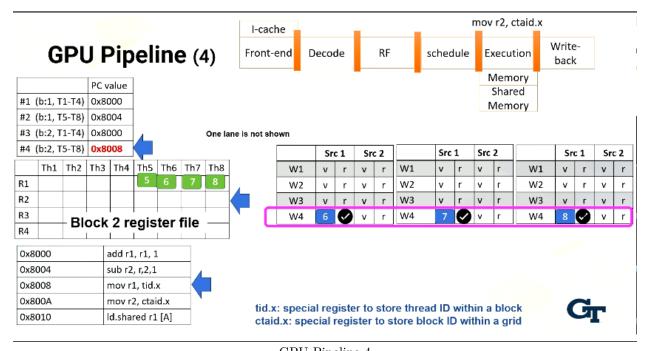
GPU Pipeline 2

GPU Pipeline 3



GPU Pipeline

## GPU Pipeline 4



GPU Pipeline 4

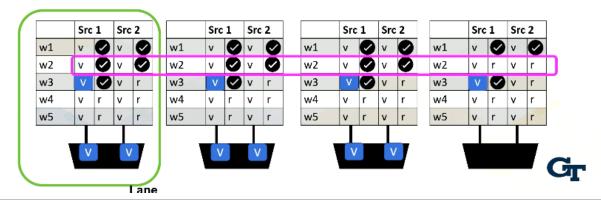
#### Mask Bits

- 1. What if we do not need to execute all 4 threads?
  - Mask bits tell us which threads are active

# Mask Bits

- What if we do not need to execute all 4 threads?
- · Mask bits tell which threads are active.

id	Mask bit				
w1	1111				
w2	1110				
w3	0111				
w4	1111				
w5	1111				



Mask Bits

## Summary

- 1. Reviewed the GPU pipeline's instruction flow
- $2.\,$  Highlighted the use of special registers for thread ID and block ID
- 3. Introduced the concept of an active mask for identifying active SIMT lanes

# **Global Memory Coalescing**

#### Learning Objectives

- 1. Explore global memory accesses
- 2. Explain memory address coalescing
- 3. Describe how one warp can generate multiple memory requests

# Global Memory Accesses

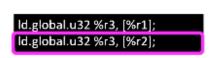
- 1. 1 memory instruction could generate many memory requests to DRAM
- 2. 1 warp can generate up to 32 memory requests (if warp size is 32)
- 3. Number of requests can easily be a large number
  - $32 \text{ SMs} \rightarrow 32 * 32 = 1024 \text{ requests in one cycle}$
  - 1024 \* 64B = 64KB per cycle (1 GHz GPU) -> 64 TB/s memory bandwidth

## DRAM vs SRAM

- 1. SRAM: 6 transistors
  - Used in caches
  - Maintains charge over time
- 2. DRAM: 1 transistor (capacitor)
  - Loses charge over time, must be refreshed
- 3. GPU with High-Bandwidth Memory (HBM)
  - 3D-stack of DRAM with silicon interposer to interface
  - HBM provides significant memory bandwidth

## **Memory Coalescing**

- 1. Even if the memory can provide high bandwidth memory, reducing memory requests is critical
- 2. GPU cache is very small
- 3. DRAM memory requests size is 64  $\sim 128 B$
- 4. All memory requests from the first load can be combined into one memory request
  - $mem[0] + 28 \rightarrow called coalesced$
  - Second load cannot be easily combined -> uncoalesced



	Th1	Th2	Th3	Th4	Th5	Th6	Th7	Th8
R1	0	4	8	12	16	18	20	24
R2	0	128	256	512	768	1024	1152	1280
R3								
R4								

Memory Coalescing

## Coalesced Memory

- 1. Combining multiple memory requests into a single or more efficient memory request
- 2. Consecutive memory requests can be coalesced
- 3. Reduce the total number of memory requests
- 4. One of the key software optimization techniques

#### Summary

- 1. Uncoalesced global memory requests significantly degrade performance
- 2. GPUs have the potential to saturate memory bandwidth
- 3. Coalescing memory requests is crucial for efficient memory access and better GPU performance