CUDA Optimization

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Outline

- Kernel optimizations
 - Global memory throughput
 - Launch configuration
 - Instruction throughput / control flow
 - Shared memory access
- Optimizations of CPU-GPU interaction
 - Maximizing PCIe throughput
 - Overlapping kernel execution with memory copies

Global Memory Throuhgput

Memory Review

- Local storage
 - Each thread has own local storage
 - Mostly registers (managed by the compiler)
- Shared memory
 - Each thread block has own shared memory
 - Very low latency (a few cycles)
 - Very high throughput: 38-44 GB/s per multiprocessor
 - 30 multiprocessors per GPU -> over 1.1 TB/s
- Global memory
 - Accessible by all threads as well as host (CPU)
 - High latency (400-800 cycles)
 - Throughput: 140 GB/s (1GB boards), 102 GB/s (4GB boards)

GMEM Coalescing: Compute Capability 1.2, 1.3

• Possible GPU memory bus transaction sizes:

- 32B, 64B, or 128B
- Transaction segment must be aligned
 - First address = multiple of segment size

• Hardware coalescing for each half-warp (16 threads):

- Memory accesses are handled per half-warps
- Carry out the smallest possible number of transactions
- Reduce transaction size when possible



64B segment





64B segment

32B

segment

HW Steps when Coalescing

- Find the memory segment that contains the address requested by the lowest-numbered active thread:
 - 32B segment for 8-bit data
 - 64B segment for 16-bit data
 - 128B segment for 32, 64 and 128-bit data.
- Find all other active threads whose requested address lies in the same segment
- Reduce the transaction size, if possible:
 - If size = 128B and only the lower or upper half is used, reduce transaction to 64B
 - If size = 64B and only the lower or upper half is used, reduce transaction to 32B
 - Applied even if 64B was a reduction from 128B
- Carry out the transaction, mark serviced threads as inactive
- Repeat until all threads in the half-warp are serviced



64B segment





64B segment

32B

segment

- Thread 0 is lowest active, accesses address 116
- 128-byte segment: 0-127



- Thread 0 is lowest active, accesses address 116
- 128-byte segment: 0-127 (reduce to 64B)



- Thread 0 is lowest active, accesses address 116
- 128-byte segment: 0-127 (reduce to 32B)



- Thread 3 is lowest active, accesses address 128
- 128-byte segment: 128-255



- Thread 3 is lowest active, accesses address 128
- 128-byte segment: 128-255 (reduce to 64B)



Experiment: Impact of Address Alignment

- Assume half-warp accesses a contiguous region
- Throughput is maximized when region is aligned on its size boundary
 - 100% of bytes in a bus transaction are useful
- Impact of misaligned addressing:
 - 32-bit words, streaming code, Quadro FX5800 (102 GB/s)
 - 0 word offset: 76 GB/s (perfect alignment, typical perf)
 - 8 word offset: 57 GB/s (75% of aligned case)
 - All others: 46 GB/s (61% of aligned case)

Address Alignment, 64-bit words

- Can be analyzed similarly to 32-bit case:
 - OB offset: 80 GB/s (perfectly aligned)
 - 8B offset: 62 GB/s (78% of perfectly aligned)
 - 16B offset: 62 GB/s (78% of perfectly aligned)
 - 32B offset: 68 GB/s (85% of perfectly aligned)
 - 64B offset: 76 GB/s (95% of perfectly aligned)
- Compare 0 and 64B offset performance:
 - Both consume 100% of the bytes
 - 64B: two 64B transactions
 - OB: a single 128B transaction, slightly faster

Comparing Compute Capabilities

• Compute capability < 1.2

- Requires threads in a half-warp to:
 - Access a single aligned 64B, 128B, or 256B segment
 - Threads must issue addresses in sequence
- If requirements are not satisfied:
 - Separate 32B transaction for each thread

• Compute capability 1.2 and 1.3

- Does not require sequential addressing by threads
- Perf degrades gracefully when a half-warp addresses multiple segments

• Compute capability 2.0 (Fermi)

- Memory access is per warp (32 threads), L1/L2 caches help with alignment

GMEM Optimization Guidelines

Strive for perfect coalescing

- Align starting address (may require padding)
- Warp should access within contiguous region

• Process several elements per thread

- Multiple loads get pipelined
- Indexing calculations can often be reused
- Launch enough threads to cover access latency
 - GMEM accesses are not cached
 - Latency is hidden by switching threads (warps)

Data Layout for Optimal Memory Throughput

• Prefer Structure of Arrays instead of Array of Structures:

- A warp (32 threads) should be accessing a contiguous memory region
 - As opposed to a thread accessing a contiguous region (as is often the case on CPU)
- Stride between threads in a warp will ideally be 1, 2, 4, 8, or 16B (goes back to how hw coalescing is done)
- Not that different from what has to be done for CPU vectorization:
 - SSE: 4-wide vectors (for fp32)
 - One can think of GPU accesses as 32-wide vectors

Global Memory Throughput Metric

- Many applications are memory throughput bound
- When coding from scratch:
 - Start with memory operations first, achieve good throughput
 - Add the arithmetic, measuring perf as you go
- When optimizing:
 - Measure effective memory throughput
 - Compare to the theoretical bandwidth
 - 70-80% is very good, ~50% is good if arithmetic is nontrivial
- Measuring throughput
 - From the app point of view ("useful" bytes)
 - From the hw point of view (actual bytes moved across the bus)
 - The two are likely to be different
 - Due to coalescing, discrete bus transaction sizes

Measuring Memory Throughput

- Visual Profiler reports memory throughput
 - From HW point of view
 - Based on counters for one TPC (3 multiprocessors)
 - Need compute capability 1.2 or higher GPU

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	Profiler Output 🛛 🔛 🛛	5ummary Table	×				
	Method	GPU 🚽 usec	%GPU time	glob mem read throughput (GB/s)	glob mem write throughput (GB/s)	glob mem overall throughput (GB/s)	instruction throughput
1	[fwd_3D_16×16_order8]	3.09382e+06	82.15	46.9465	11.6771	58.6236	0.763973
2	memcpyHtoD	503094	13.35				
3	memcpyDtoH	168906	4.48				

Measuring Memory Throughput

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• How throughput is computed:

- Count load/store bus transactions of each size (32, 64, 128B) on the TPC
- Extrapolate from one TPC to the entire GPU
 - Multiply by (total threadblocks / threadblocks on TPC)

(grid size / cta launched)

Launch Configuration

Launch Configuration

- How many threads/threadblocks to launch?
- Key to understanding:
 - Instructions are issued in order
 - A thread blocks when one of the operands isn't ready:
 - Memory read doesn't block
 - Latency is hidden by switching threads
 - Not by cache
 - GMEM latency is 400-800 cycles
- Conclusion:
 - Need enough threads to hide latency

Hiding Latency

Arithmetic:

Need at least 6 warps (192) threads per SM

Hiding Latency

- Arithmetic:
 - Need at least 6 warps (192) threads per SM
- Memory:
 - Depends on the access pattern
 - For GT200, 50% occupancy (512 threads per SM) is often sufficient
 - Occupancy = fraction of the maximum number of threads per multiprocessor

Streaming 16M words: each thread reads, increments, writes 1 element





Launch Configuration: Summary

- Need enough total threads to keep GPU busy
 - Currently (GT200), 512+ threads per SM is ideal
 - Fewer than 192 threads per SM WILL NOT hide arithmetic latency
- Threadblock configuration
 - Threads per block should be a multiple of warp size (32)
 - SM can concurrently execute up to 8 threadblocks
 - Really small threadblocks prevent achieving good occupancy
 - Really large threadblocks are less flexible
 - I generally use 128-256 threads/block, but use whatever is best for the application

Instruction Throughput / Control Flow

Runtime Math Library and Intrinsics

- Two types of runtime math library functions
 - __func(): many map directly to hardware ISA
 - Fast but lower accuracy (see CUDA Programming Guide for full details)
 - Examples: <u>__sinf(x)</u>, <u>__expf(x)</u>, <u>__powf(x, y)</u>
 - func(): compile to multiple instructions
 - Slower but higher accuracy (5 ulp or less)
 - Examples: sin(x), exp(x), pow(x, y)
- A number of additional intrinsics:
 - ___sincosf(), ___frcp_rz(), ...
 - Explicit IEEE rounding modes (rz,rn,ru,rd)

Control Flow

- Instructions are issued per 32 threads (warp)
- Divergent branches:
 - Threads within a single warp take different paths

• if-else, ...

- Different execution paths within a warp are serialized
- Different warps can execute different code with no impact on performance
- Avoid diverging within a warp
 - Example with divergence:
 - if (threadIdx.x > 2) {...} else {...}
 - Branch granularity < warp size
 - Example without divergence:
 - if (threadIdx.x / WARP_SIZE > 2) {...} else {...}
 - Branch granularity is a whole multiple of warp size

Profiler and Instruction Throughput

- Profiler counts per multiprocessor:
 - Divergent branches
 - Warp serialization
 - Instructions issues
- Visual Profiler derives:
 - Instruction throughput
 - Fraction of SP arithmetic instructions that could have been issued in the same amount of time
 - So, not a good metric for code with DP arithmetic or transcendentals
 - Extrapolated from one multiprocessor to GPU

Profiler and Instruction Throughput

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Shared Memory

Shared Memory

- Uses:
 - Inter-thread communication within a block
 - Cache data to reduce redundant global memory accesses
 - Use it to avoid non-coalesced access
- Organization:
 - 16 banks, 32-bit wide banks
 - Successive 32-bit words belong to different banks
- Performance:
 - 32 bits per bank per 2 clocks per multiprocessor
 - smem accesses are per 16-threads (half-warp)
 - serialization: if n threads (out of 16) access the same bank, n accesses are executed serially
 - broadcast: *n* threads access the same word in one fetch

Bank Addressing Examples



Bank Addressing Examples



Trick to Assess Impact On Performance

- Change all SMEM reads to the same value
 - All broadcasts = no conflicts
 - Will show how much performance can be improved by eliminating bank conflicts
- The same doesn't work for SMEM writes
 - So, replace SMEM array indices with threadIdx.x
 - Can also be done to the reads

CPU-GPU Interaction

Pinned (non-pageable) memory

• Pinned memory enables:

- faster PCIe copies (~2x throughput on FSB systems)
- memcopies asynchronous with CPU
- memcopies asynchronous with GPU
- Usage
 - cudaHostAlloc / cudaFreeHost
 - instead of malloc / free
- Implication:

- pinned memory is essentially removed from host virtual memory

Streams and Async API

• Default API:

- Kernel launches are asynchronous with CPU
- Memcopies (D2H, H2D) block CPU thread
- CUDA calls are serialized by the driver
- Streams and async functions provide:
 - Memcopies (D2H, H2D) asynchronous with CPU
 - Ability to concurrently execute a kernel and a memcopy
- Stream = sequence of operations that execute in issue-order on GPU
 - Operations from different streams can be interleaved
 - A kernel and memcopy from different streams can be overlapped

Overlap kernel and memory copy

• Requirements:

- D2H or H2D memcopy from pinned memory
- Device with compute capability \geq 1.1 (G84 and later)
- Kernel and memcopy in different, non-0 streams

• Code:

cudaStream_t stream1, stream2;

cudaStreamCreate(&stream1);

cudaStreamCreate(&stream2);

cudaMemcpyAsync(dst, src, size, dir, stream1);
kernel<<<grid, block, 0, stream2>>>(...);

potentially
overlapped

Call Sequencing for Optimal Overlap

- CUDA calls are dispatched to the hw in the sequence they were issued
- A call is dispatched if both are true:
 - Resources are available
 - Preceding calls in the same stream have completed
- One kernel and one memcopy can be executed concurrently
- Note that if a call blocks, it blocks all other calls of the same type behind it, even in other streams
 - Type is one of { kernel, memcopy }

Stream Examples (current HW)



Summary

- GPU-CPU interaction:
 - Minimize CPU/GPU idling, maximize PCIe throughput
- Global memory:
 - Maximize throughput (GPU has lots of bandwidth, use it effectively)
- Kernel Launch Configuration:
 - Launch enough threads per SM to hide latency
 - Launch enough threadblocks to load the GPU

Summary

- GPU-CPU interaction:
 - Minimize CPU/GPU idling, maximize PCIe throughput
- Global memory:
 - Maximize throughput (GPU has lots of bandwidth, use it effectively)
- Kernel Launch Configuration:
 - Launch enough threads per SM to hide latency
 - Launch enough threadblocks to load the GPU
- Measure!
 - Use the Profiler, simple code modifications
 - Compare to theoretical peaks