

KAUST

CS 380 - GPU and GPGPU Programming Lecture 24: CUDA Memory, Pt. 3

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Reading Assignment #13 (until Nov 27)

Read (required):

• Optimizing Parallel Reduction in CUDA, Mark Harris,

https://developer.download.nvidia.com/assets/cuda/files/reduction.pdf

Programming Massively Parallel Processors book, 4th edition
 Chapter 8: Prefix Sum (Scan) – work efficiency in parallel algorithms

Read (optional):

- Programming Massively Parallel Processors book, 4th edition Chapter 7: Reduction
- GPU Gems 3 book, Chapter 39: Parallel Prefix Sum (Scan) with CUDA https://developer.nvidia.com/gpugems/GPUGems3/gpugems3_ch39.html
- Faster Parallel Reductions on Kepler, Justin Luitjens https://devblogs.nvidia.com/parallelforall/faster-parallel-reductions-kepler/

CUDA Memory: Shared Memory

Memory and Cache Types



Global memory

- [Device] L2 cache
- [SM] **L1 cache** (shared mem carved out; *or* L1 shared with tex cache)
- [SM/TPC] **Texture cache** (separate, or shared with L1 cache)
- [SM] **Read-only data cache** (storage might be same as tex cache)

Shared memory

• [SM] Shareable only between threads in same thread block (Hopper/CC 9.x: also thread block clusters)

Constant memory: Constant (uniform) cache

Unified memory programming: Device/host memory sharing

Memory Banks

Fermi/Kepler/Maxwell and newer:

32 banks

default: 4B / bank

Kepler or newer: configurable to 8B / bank



Shared Memory

Uses:

- Inter-thread communication within a block
- Cache data to reduce redundant global memory accesses
- Use it to improve global memory access patterns

Performance:

- smem accesses are issued per warp
- Throughput is 4 (or 8) bytes per bank per clock per multiprocessor
- serialization: if *N* threads of 32 access different words in the same bank,
 N accesses are executed serially
- multicast: N threads access the same word in one fetch
 - Could be different bytes within the same word

Bank Addressing Examples



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Bank Addressing Examples



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How addresses map to banks on G80

- Each bank has a bandwidth of 32 bits per clock cycle
- Successive 32-bit words are assigned to successive banks
- G80 has 16 banks
 - So bank = address % 16
 - Same as the size of a half-warp
 - No bank conflicts between different half-warps, only within a single half-warp

Fermi and newer have 32 banks, considers full warps instead of half warps!

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Shared Memory Bank Conflicts

- Shared memory is as fast as registers if there are no bank conflicts
- The fast case:
 - If all threads of a half-warp access different banks, there is no bank conflict
 - If all threads of a half-warp access the identical address, there is no bank conflict (broadcast)
- The slow case:
 - Bank Conflict: multiple threads in the same half-warp access the same bank
 - Must serialize the accesses
 - Cost = max # of simultaneous accesses to a single bank

full warps instead of half warps on Fermi and newer!

Linear Addressing

• Given:

```
__shared__ float shared[256];
float foo =
   shared[baseIndex + s * threadIdx.x];
```

- This is only bank-conflict-free if s shares no common factors with the number of banks
 - 16 on G80, so s must be odd





Parallel08 – Memory Access

Hendrik Lensch and Robert Strzodka

Data Types and Bank Conflicts

• This has no conflicts if type of shared is 32-bits:

foo = shared[baseIndex + threadIdx.x]

But not if the data type is smaller

```
- 4-way bank conflicts:
__shared__ char shared[];
foo = shared[baseIndex + threadIdx.x];
```

but no problem on Fermi or newer: multi-cast!

- 2-way bank conflicts: __shared__ short shared[]; foo = shared[baseIndex + threadIdx.x];

but no problem on Fermi or newer: multi-cast!





Structs and Bank Conflicts

 Struct assignments compile into as many memory accesses as there are struct members:



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Broadcast on Shared Memory

 Each thread loads the same element – no bank conlict

 $\mathbf{x} = \text{shared}[0];$

• Will be resolved implicitly

multi-cast on Fermi and newer!



Common Array Bank Conflict Patterns 1D

- Each thread loads 2 elements into shared mem:
 - 2-way-interleaved loads result in 2-way bank conflicts:

int tid = threadIdx.x; shared[2*tid] = global[2*tid]; shared[2*tid+1] = global[2*tid+1];

- This makes sense for traditional CPU threads, locality in cache line usage and reduced sharing traffic.
 - Not in shared memory usage where there is no cache line effects but banking effects



A Better Array Access Pattern

 Each thread loads one element in every consecutive group of blockDim elements.

shared[tid] = global[tid];
shared[tid + blockDim.x] =
global[tid + blockDim.x];



OPTIMIZE

Kernel Optimizations: Shared Memory Accesses

Case Study: Matrix Transpose

- Coalesced read
- Scattered write (stride N)
- ⇒ Process matrix tile, not single row/column, per block
- \Rightarrow Transpose matrix tile within block



Case Study: Matrix Transpose

- Coalesced read
- Scattered write (stride N)
- Transpose matrix tile within block
- ⇒ Need threads in a block to cooperate: use shared memory



Transpose with coalesced read/write

global transpose(float in[], float out[])

```
shared float tile[TILE][TILE];
```

```
int glob_in = xIndex + (yIndex)*N;
int glob out = xIndex + (yIndex)*N;
```

tile[threadIdx.y][threadIdx.x] = in[glob in];

```
syncthreads();
```

ł

}

out[glob out] = tile[threadIdx.x][threadIdx.y];

Fixed GMEM coalescing, but introduced SMEM bank conflicts

transpose<<<grid, threads>>>(in, out);

Shared Memory: Avoiding Bank Conflicts

- Example: 32x32 SMEM array
- Warp accesses a column:
 - 32-way bank conflicts (threads in a warp access the same bank)



Shared Memory: Avoiding Bank Conflicts

Add a column for padding:

32x33 SMEM array

Warp accesses a column:

32 different banks, no bank conflicts

Bank 0 Bank 1 Bank 31



Thank you.