GPU Memory

— Memory issue for CUDA programming
### CUDA Variable Type Qualifiers

<table>
<thead>
<tr>
<th>Variable declaration</th>
<th>Memory</th>
<th>Scope</th>
<th>Lifetime</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>device</strong> <strong>local</strong> int LocalVar;</td>
<td>local</td>
<td>thread</td>
<td>thread</td>
</tr>
<tr>
<td><strong>device</strong> <strong>shared</strong> int SharedVar;</td>
<td>shared</td>
<td>block</td>
<td>block</td>
</tr>
<tr>
<td><strong>device</strong> int GlobalVar;</td>
<td>global</td>
<td>grid</td>
<td>application</td>
</tr>
<tr>
<td><strong>device</strong> <strong>constant</strong> int ConstantVar;</td>
<td>constant</td>
<td>grid</td>
<td>application</td>
</tr>
</tbody>
</table>

- **__device__** is optional when used with **__local__**, **__shared__**, or **__constant__**

- **Automatic variables** without any qualifier reside in a register
  - Except arrays that reside in local memory
Where to declare variables?

Can host access it?

yes

no

register (automatic) shared local

global constant

Outside of any Function

In the kernel

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Variable Type Restrictions

- **Pointers** can only point to memory allocated or declared in global memory:
  - Allocated in the host and passed to the kernel:
    ```c
    __global__ void KernelFunc(float* ptr)
    ```
  - Obtained as the address of a global variable:
    ```c
    float* ptr = &GlobalVar;
    ```
A Common Programming Strategy

- Global memory is much slower than shared memory
- So, a profitable way of performing computation on the device is to **tile data** to take advantage of fast shared memory:
  - Partition data into subsets that fit into shared memory
  - Handle each data subset with one thread block by:
    - Loading the subset from global memory to shared memory, using multiple threads to exploit memory-level parallelism
    - Performing the computation on the subset from shared memory; each thread can efficiently multi-pass over any data element
    - Copying results from shared memory to global memory
A Common Programming Strategy (Cont.)

- Constant memory also resides in device memory - much slower access than shared memory
  - But... cached!
  - Highly efficient access for read-only data

- Carefully divide data according to access patterns
  - R/Only → constant memory (very fast if in cache)
  - R/W shared within Block → shared memory (very fast)
  - R/W within each thread → registers (very fast)
  - R/W inputs/results → global memory (very slow)

For texture memory usage, see NVIDIA document.
GPU Atomic Integer Operations

- Atomic operations on integers in global memory:
  - Associative operations on signed/unsigned ints
  - add, sub, min, max, ...
  - and, or, xor
  - Increment, decrement
  - Exchange, compare and swap
- Requires hardware with compute capability 1.1 and above.
Shared Memory

- Matrix Multiplication as example again.
Review: Matrix Multiplication Kernel using Multiple Blocks

```c
__global__ void MatrixMulKernel(float* Md, float* Nd, float* Pd, int Width)
{
    // Calculate the row index of the Pd element and M
    int Row = blockIdx.y*TILE_WIDTH + threadIdx.y;
    // Calculate the column index of Pd and N
    int Col = blockIdx.x*TILE_WIDTH + threadIdx.x;

    float Pvalue = 0;
    // each thread computes one element of the block sub-matrix
    for (int k = 0; k < Width; ++k)
        Pvalue += Md[Row*Width+k] * Nd[k*Width+Col];

    Pd[Row*Width+Col] = Pvalue;
}
```
How about performance on G80?

- All threads access global memory for their input matrix elements
  - Two memory accesses (8 bytes) per floating point multiply-add
  - 4B/s of memory bandwidth/FLOPS
  - $4 \times 346.5 = 1386$ GB/s required to achieve peak FLOP rating
  - 86.4 GB/s limits the code at 21.6 GFLOPS
- Need to drastically cut down memory accesses to get closer to the peak 346.5 GFLOPS
Idea: Use Shared Memory to reuse global memory data

- Each input element is read by $\text{WIDTH}$ threads.
- Load each element into Shared Memory and have several threads use the local version to reduce the memory bandwidth
  - Tiled algorithms
Break up the execution of the kernel into phases so that the data accesses in each phase is focused on one subset (tile) of \( \text{Md} \) and \( \text{Nd} \).
Example

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**Example (Cont’)**

- Every Md and Nd Element is used exactly twice in generating a 2X2 tile of $P$

<table>
<thead>
<tr>
<th></th>
<th>$P_{0,0}$ thread$_{0,0}$</th>
<th>$P_{1,0}$ thread$_{1,0}$</th>
<th>$P_{0,1}$ thread$_{0,1}$</th>
<th>$P_{1,1}$ thread$_{1,1}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>M$<em>{0,0}$ * N$</em>{0,0}$</td>
<td>M$<em>{0,0}$ * N$</em>{1,0}$</td>
<td>M$<em>{0,1}$ * N$</em>{0,0}$</td>
<td>M$<em>{0,1}$ * N$</em>{1,0}$</td>
<td></td>
</tr>
<tr>
<td>M$<em>{1,0}$ * N$</em>{0,1}$</td>
<td>M$<em>{1,0}$ * N$</em>{1,1}$</td>
<td>M$<em>{1,1}$ * N$</em>{0,1}$</td>
<td>M$<em>{1,1}$ * N$</em>{1,1}$</td>
<td></td>
</tr>
<tr>
<td>M$<em>{2,0}$ * N$</em>{0,2}$</td>
<td>M$<em>{2,0}$ * N$</em>{1,2}$</td>
<td>M$<em>{2,1}$ * N$</em>{0,2}$</td>
<td>M$<em>{2,1}$ * N$</em>{1,2}$</td>
<td></td>
</tr>
<tr>
<td>M$<em>{3,0}$ * N$</em>{0,3}$</td>
<td>M$<em>{3,0}$ * N$</em>{1,3}$</td>
<td>M$<em>{3,1}$ * N$</em>{0,3}$</td>
<td>M$<em>{3,1}$ * N$</em>{1,3}$</td>
<td></td>
</tr>
</tbody>
</table>

Access order:

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Breaking Md and Nd into Tiles
Each phase of a Thread Block uses one tile from $\mathbf{Md}$ and one from $\mathbf{Nd}$

<table>
<thead>
<tr>
<th>Time</th>
<th>$\mathbf{Md}$</th>
<th>$\mathbf{Nd}$</th>
<th>Step 4</th>
<th>Step 5</th>
<th>Step 6</th>
</tr>
</thead>
<tbody>
<tr>
<td>$T_{0,0}$</td>
<td>$\mathbf{Md}_{0,0}$</td>
<td>$\mathbf{Nd}_{0,0}$</td>
<td>$\mathbf{PValue}<em>{0,0} + = \mathbf{Mds}</em>{0,0} * \mathbf{Nds}<em>{0,0} + \mathbf{Mds}</em>{1,0} * \mathbf{Nds}_{1,1}$</td>
<td>$\mathbf{Md}_{2,0}$</td>
<td>$\mathbf{Nd}_{0,2}$</td>
</tr>
<tr>
<td>$T_{1,0}$</td>
<td>$\mathbf{Md}_{1,0}$</td>
<td>$\mathbf{Nd}_{1,0}$</td>
<td>$\mathbf{PValue}<em>{1,0} + = \mathbf{Mds}</em>{0,0} * \mathbf{Nds}<em>{1,0} + \mathbf{Mds}</em>{1,0} * \mathbf{Nds}_{1,1}$</td>
<td>$\mathbf{Md}_{3,0}$</td>
<td>$\mathbf{Nd}_{1,2}$</td>
</tr>
<tr>
<td>$T_{0,1}$</td>
<td>$\mathbf{Md}_{0,1}$</td>
<td>$\mathbf{Nd}_{0,1}$</td>
<td>$\mathbf{PdValue}<em>{0,1} + = \mathbf{Mds}</em>{0,1} * \mathbf{Nds}<em>{0,0} + \mathbf{Mds}</em>{1,1} * \mathbf{Nds}_{1,1}$</td>
<td>$\mathbf{Md}_{2,1}$</td>
<td>$\mathbf{Nd}_{0,3}$</td>
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<tr>
<td>$T_{1,1}$</td>
<td>$\mathbf{Md}_{1,1}$</td>
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<td>$\mathbf{PdValue}<em>{1,1} + = \mathbf{Mds}</em>{0,1} * \mathbf{Nds}<em>{1,0} + \mathbf{Mds}</em>{1,1} * \mathbf{Nds}_{1,1}$</td>
<td>$\mathbf{Md}_{3,1}$</td>
<td>$\mathbf{Nd}_{1,3}$</td>
</tr>
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</table>
First-order Size Considerations in G80

- Each thread block should have many threads
  - TILE_WIDTH of 16 gives $16 \times 16 = 256$ threads

- There should be many thread blocks
  - A $1024 \times 1024$ Pd gives $64 \times 64 = 4096$ Thread Blocks

- Each thread block perform $2 \times 256 = 512$ float loads from global memory for $256 \times (2 \times 16) = 8,192$ mul/add operations.
  - Memory bandwidth no longer a limiting factor
CUDA Code – Kernel Execution Configuration

// Setup the execution configuration
dim3 dimBlock(TILE_WIDTH, TILE_WIDTH);
dim3 dimGrid(Width / TILE_WIDTH, Width / TILE_WIDTH);
__global__ void MatrixMulKernel(float* Md, float* Nd, float* Pd, int Width) 
{
  __shared__ float Mds[TILE_WIDTH][TILE_WIDTH];
  __shared__ float Nds[TILE_WIDTH][TILE_WIDTH];

  int bx = blockIdx.x;  int by = blockIdx.y;
  int tx = threadIdx.x; int ty = threadIdx.y;

  // Identify the row and column of the Pd element to work on
  int Row = by * TILE_WIDTH + ty;
  int Col = bx * TILE_WIDTH + tx;

  float Pvalue = 0;
  // Loop over the Md and Nd tiles required to compute the Pd element
  for (int m = 0; m < Width/TILE_WIDTH; ++m) {
    // Collaborative loading of Md and Nd tiles into shared memory
    Mds[ty][tx] = Md[Row*Width + (m*TILE_WIDTH + tx)];
    Nds[ty][tx] = Nd[Col + (m*TILE_WIDTH + ty)*Width];
    __syncthreads();

    for (int k = 0; k < TILE_WIDTH; ++k)
      Pvalue += Mds[ty][k] * Nds[k][tx];
    __syncthreads();
  }
  Pd[Row*Width+Col] = Pvalue;
}
Tiled Multiply

- Each **block** computes one square sub-matrix $P_{d_{sub}}$ of size $TILE\_WIDTH$
- Each **thread** computes one element of $P_{d_{sub}}$
G80 Shared Memory and Threading

- Each SM in G80 has 16KB shared memory
  - SM size is implementation dependent!
  - For TILE_WIDTH = 16, each thread block uses 2*256*4B = 2KB of shared memory.
- Can potentially have up to 8 Thread Blocks actively executing
  - This allows up to 8*512 = 4,096 pending loads. (2 per thread, 256 threads per block)
- The next TILE_WIDTH 32 would lead to 2*32*32*4B = 8KB shared memory usage per thread block, allowing only up to two thread blocks active at the same time
- Using 16x16 tiling, we reduce the accesses to the global memory by a factor of 16
  - The 86.4B/s bandwidth can now support (86.4/4)*16 = 347.6 GFLOPS!
Tiling Size Effects

![Graph showing the effects of tiling size on GPU memory performance]

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Summary - Typical Structure of a CUDA Program

- Global variables declaration
  - __host__
  - __device__... __global__, __constant__, __texture__
- Function prototypes
  - __global__ void kernelOne(…)
  - float handyFunction(…)
- Main()
  - allocate memory space on the device – cudaMemcpy(&d_GlblVarPtr, bytes)
  - transfer data from host to device – cudaMemcpy(d_GlblVarPtr, h_Gl…)
  - execution configuration setup
  - kernel call – kernelOne<<<execution configuration>>>( args… );
  - transfer results from device to host – cudaMemcpy(h_GlblVarPtr,…)
  - optional: compare against golden (host computed) solution
- Kernel – void kernelOne(type args,…)
  - variables declaration - __local__, __shared__
  - automatic variables transparently assigned to registers or local memory
  - syncthreads()…
- Other functions
  - float handyFunction(int inVar…);