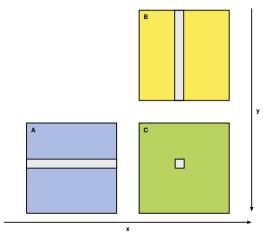


GPU PROGRAMMING WITH CUDA Matrix multiplication

April 27, 2021 | Kaveh Haghighi Mood, Jochen Kreutz | JSC



Distribution of work

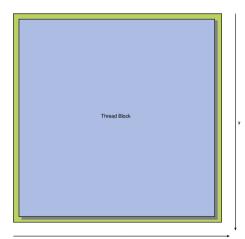


$$C_{row,col} = \sum_{i=1}^{N} A_{row,i} * B_{i,col}$$

- Each thread computes one element of the reuslt matrix C
- n * n threads will be needed (for square matrix C of size n)
- Thread indexing corresponds to 2d indexing of matrices
- Thread (x,y) will compute result element C(x,y) using row y of A and column x of B



Execution grid layout

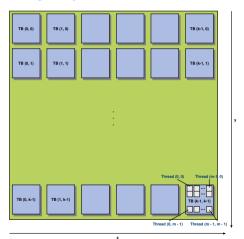


First naive idea:

- use one big thread block to cover all result elements
- Thread blocks are limited in size, thus we need several thread blocks to cover the full matrix C
- In addition, using only one thread block will decrease performance (due to reduced device occupancy)



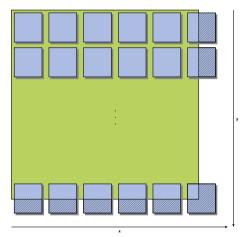
Execution grid layout



- Cover result matrix C of size n x n by using a 2d kernel execution grid with k * k thread blocks (TB)
- Use 2d thread blocks with fixed block size m
- k = n / m (n divisible by m)
- k = n / m + 1 (n not divisible by m)



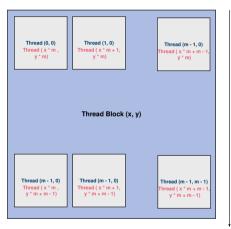
Execution grid layout



- k = n / m + 1 (n not divisible by m)
- All thread blocks have the same size
- Not possible to create "partial blocks"
- To take care that some threads might not have to do any work (avoid out ouf bound memory access!)



Execution grid layout



- Threads can be addressed via local index (block internal) and global index (full grid)
- Use available keywords in your kernel for targetting certain threads:
 - blockIdx.[x, y, z]
 - blockDim.[x, y, z]
 - threadIdx.[x, y, z]



Execution grid layout

dim3 blockDim

```
dim3 blockDim { size_t blockDimX, size_t blockDimY, size_t blockDimZ }
```

On JUWELS Booster (Nvidia A100):

- Max. dim. of a block: 1024 x 1024 x 64
- Max. number of threads per block: 1024

Example

```
// Create 3d thread block with 512 threads
dim3 blockDim (16, 16, 2);
```



Execution grid layout

dim3 gridDim

```
dim3 gridDim { size_t gridDimX, size_t gridDimY, size_t gridDimZ }
```

On JUWELS Booster (Nvidia A100):

- Max. dim. of a grid: 2147483647 x 65535 x 65535
- Use cudaGetDeviceProperties() to get device properties

```
// problem dimension: nx * ny = 1000 * 1000
dim3 blockDim (16. 16) // don't need to write z = 1
int gx = (nx % blockDim.x == 0) ? nx / blockDim.x : nx / blockDim.x + 1
int gy = (ny % blockDim.y == 0) ? ny / blockDim.y : ny / blockDim.y + 1
dim3 gridDim (gx, gy); // don't need to write z = 1
```

Calling the kernel

Define dimensions of thread blocks

dim3 blockDim { size_t blockDimX, size_t blockDimY, size_t blockDimZ }

Define dimensions of execution grid

dim3 gridDim { size_t gridDimX, size_t gridDimY, size_t gridDimZ }

Launch the kernel

kernel_name <<< dim3 gridDim, dim3 blockDim >>> ([kernel args])



Cuda kernel

```
Example
```

```
global void mm kernel(float* A, float* B, float* C, int n) {
        int col = blockIdx.x * blockDim.x + threadIdx.x:
        int row = blockIdx.y * blockDim.y + threadIdx.y;
        if (row < n \&\& col < n)
                for (int i = 0; i < n; ++i) {
                        C[row*n + col] += A[row*n + i] * B[i*n + col]:
mm kernel <<< dimGrid. dimBlock >>> (d a, d b, d c, n):
```

Simple matrix multiplication with Cuda



Location:

 $.../exercises/tasks/Cuda_MM_simple/Instructions.ipynb$



Measured numbers

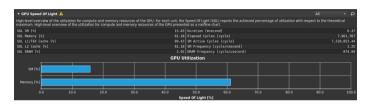
JUWELS Cluster: 1 x V100 (theoretical peak: 7 TFlops DP)

JUWELS Booster: 1 x A100 (theoretical peak: 9.7 TFlops DP, 19.5 with TC)

matrix size	64	1024	10240	64	1024	10240
	JW Cluster [gflops]			JW Booster [gflops]		
with cvalue	1.2	319	1146	1.1	286.2	1587.1
direct write	1.02	196	391	0.9	198.3	562.2



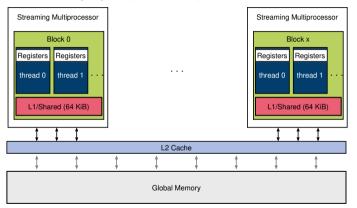
Profiler hints for simple matrix multiplication



- get useful hints from profiler
- helps to identify hotspots and potential performance issues
- get an overview timeline using Nsight Systems
- can analyse kernels individually using Nsight Compute
- indicates very low compute utilization
- dgemm kernel is memory-bound (GPU cores spend lots of time waiting for data)



GPU memory layout (schematics)

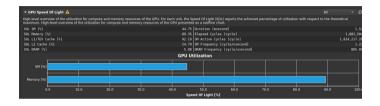




- matrix array C located in global memory
- cvalue located in registers on SM: faster write operations



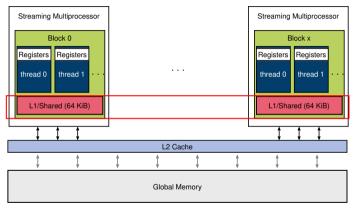
Profiler hints for simple matrix multiplication



Using cvalue reduces the access to the global memory



GPU memory layout (schematics)



what about using Shared Memory ?!



- matrix array C located in global memory
- cvalue located in registers on SM: faster write operations



SHARED MEMORY

How to use inside your kernels

Allocate shared memory

```
// allocate vector in shared memory
__shared__ float[size];
// can also define multi-dimensional arrays: BLOCK_SIZE is length (and width) of a thread
block here
```

```
__shared__ float Msub[BLOCK_SIZE][BLOCK_SIZE];
```

Copy data into shared memory

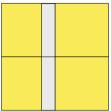
```
// fetch data from global to shared memory
```

```
Msub[threadIdx.y][threadIdx.x] = M[TidY * width + TidX];
```

Remember: only shared between threads within the same thread block!



Idea



input matrix B



input matrix A



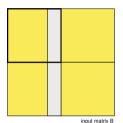
result matrix C

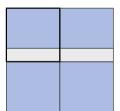
Split computation of result element into parts (assume N is even here)

$$C_{row,col} = \sum_{i=1}^{N} A_{row,i} * B_{i,col}$$

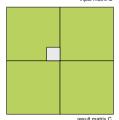


Idea





input matrix A



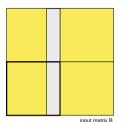
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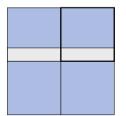
$$C_{row,col} = \sum_{i=1}^{N} A_{row,i} * B_{i,col}$$

$$=\sum_{i=1}^{\frac{N}{2}}A_{row,i}*B_{i,co}$$



Idea





input matrix A

result matrix C

Split computation of result element into parts (assume N is even here)

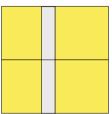
$$C_{row,col} = \sum_{i=1}^{N} A_{row,i} * B_{i,col}$$

$$=\sum_{i=1}^{\frac{N}{2}}A_{row,i}*B_{i,col}$$

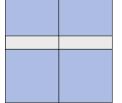
$$+\sum_{i=\frac{N}{2}+1}^{N}A_{row,i}*B_{i,col}$$



Idea



innut matrix B



input matrix A

result matrix C

$$C_{row,col} = \sum_{i=1}^{\frac{N}{2}} A_{row,i} * B_{i,col} + \sum_{i=\frac{N}{2}+1}^{N} A_{row,i} * B_{i,col}$$

consider all result elements within the same block in C:

$$C_{11} = A_{11} * B_{11} + A_{12} * B_{21}$$

$$C_{12} = A_{11} * B_{12} + A_{12} * B_{22}$$

$$C_{21} = A_{21} * B_{11} + A_{22} * B_{21}$$

$$C_{22} = A_{21} * B_{12} + A_{22} * B_{21}$$



Example

$$C = A * B$$

$$A = \begin{pmatrix} \begin{pmatrix} 1 & 2 \\ 4 & 1 \end{pmatrix} & \begin{pmatrix} 3 & 4 \\ 2 & 3 \end{pmatrix} \\ \begin{pmatrix} 3 & 4 \\ 2 & 3 \end{pmatrix} & \begin{pmatrix} 1 & 2 \\ 4 & 1 \end{pmatrix} \end{pmatrix}$$

$$C = \begin{pmatrix} C_{11} & C_{12} \\ C_{21} & C_{22} \end{pmatrix}$$

$$B = \begin{pmatrix} \begin{pmatrix} -9 & 11 \\ 1 & -9 \end{pmatrix} & \begin{pmatrix} 1 & 1 \\ 11 & 1 \end{pmatrix} \\ \begin{pmatrix} 1 & 1 \\ 11 & 1 \end{pmatrix} & \begin{pmatrix} -9 & 11 \\ 1 & -9 \end{pmatrix} \end{pmatrix} * \frac{1}{40}$$

Slide 18124

$$C_{11} = \begin{pmatrix} 1 & 2 \\ 4 & 1 \end{pmatrix} * \frac{1}{40} \begin{pmatrix} -9 & 11 \\ 1 & -9 \end{pmatrix} + \begin{pmatrix} 3 & 4 \\ 2 & 3 \end{pmatrix} * \frac{1}{40} \begin{pmatrix} 1 & 1 \\ 11 & 1 \end{pmatrix}$$

(1)



Example

$$C = A * B$$

$$A = \begin{pmatrix} \begin{pmatrix} 1 & 2 \\ 4 & 1 \end{pmatrix} & \begin{pmatrix} 3 & 4 \\ 2 & 3 \end{pmatrix} \\ \begin{pmatrix} 3 & 4 \\ 2 & 3 \end{pmatrix} & \begin{pmatrix} 1 & 2 \\ 4 & 1 \end{pmatrix} \end{pmatrix}$$

$$C = \begin{pmatrix} C_{11} & C_{12} \\ C_{21} & C_{22} \end{pmatrix}$$

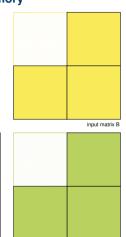
$$B = \begin{pmatrix} \begin{pmatrix} -9 & 11 \\ 1 & -9 \end{pmatrix} & \begin{pmatrix} 1 & 1 \\ 11 & 1 \end{pmatrix} \\ \begin{pmatrix} 1 & 1 \\ 11 & 1 \end{pmatrix} & \begin{pmatrix} -9 & 11 \\ 1 & -9 \end{pmatrix} \end{pmatrix} * \frac{1}{40}$$

$$= \quad \frac{1}{40}*\begin{pmatrix} -7 & -7 \\ -35 & 35 \end{pmatrix} + \frac{1}{40}*\begin{pmatrix} 47 & 7 \\ 35 & 5 \end{pmatrix} = \frac{1}{40}*\begin{pmatrix} 40 & 0 \\ 0 & 40 \end{pmatrix} = \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix}$$

do C_{12} , C_{21} and C_{22} the same way



Using shared memory



consider all result elements within the same block:

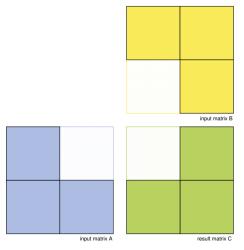
 all threads dealing with those elements will have to access input data from the same blocks of A and B for the first part of the computation



input matrix A

result matrix C

Using shared memory

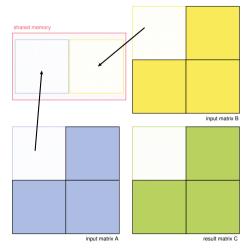


consider all result elements within the same block:

- all threads dealing with those elements will have to access input data from the same blocks of A and B for the first part of the computation
- same counts for the successing compute parts



Using shared memory

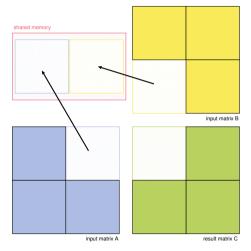


consider all result elements within the same block:

- all threads dealing with those elements will have to access input data from the same blocks of A and B for the first part of the computation
- same counts for the successing compute parts
- hence store a data copy of the input blocks into shared memory
- this prevents repeated reads from the global memory



Using shared memory

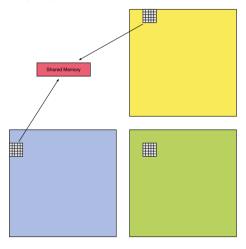


consider all result elements within the same block:

- mapping logical matrix blocks to your Cuda thread blocks ensures that all threads in your result blocks see the same shared memory
- each thread reads 1 element of A and 1 element of B and stores in into the shared memory



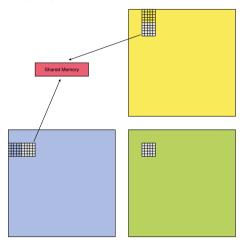
Workflow



- set result element to zero
- for each pair of blocks
 - copy input data to shared memory (one element from A and B)
 - do partial sum using shared memory
 - add partial sum to result element



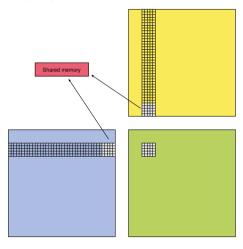
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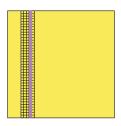
Workflow

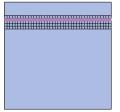


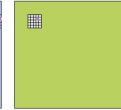
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Workflow



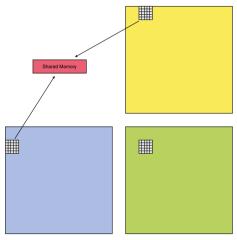




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Thread synchronization



Thread synchronization

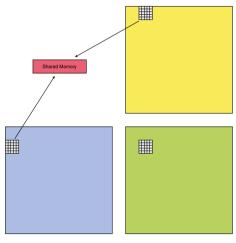
Threads within a thread block might be executed one after the other. Hence, synchronization is needed!

Synchronize threads within a thread block

__syncthreads ();



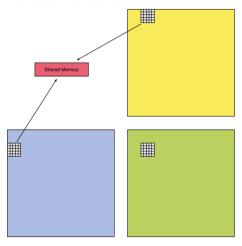
Thread synchronization



- set result element to zero
- for each pair of blocks
 - copy input data to shared memory (one element from A and B)
 - wait until all threads have copied their data
 - do partial sum
 - wait until all threads finished computation on current data
 - add partial sum to result element



Offsets and indexes



idea: use (2d coordinates of) upper left corner of input blocks as reference

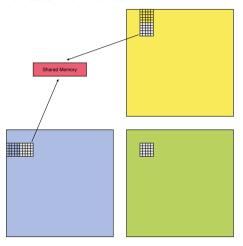
 relative positions inside the input blocks correspond to the local (block internal) thread indexes

starting point:

- row in A (blockAy): blockIdx.y * block_size
- col in B (blockBx): blockidx.x * block_size
- blockAx and blockBy will be 0 at start



Offsets and indexes



idea: use (2d coordinates of) upper left corner of input blocks as reference

moving input blocks:

- A moving to x direction by adding: block_size
- B moving to y direction by adding:
 n * block size

shared memory blocks:

 use local (block internal) thread indexes to select correct row and column



Matrix multiplication with Cuda using shared memory



Location:

.../exercises/tasks/Cuda_MM_shared/Instructions.ipynb



Measured numbers

Results on JUWELS Booster (gflops):

matrix size	1024	4096	8192	16384
Simple	286	1186	1554	1769
Shared memory(16,16)	296	952	1560	1742
Shared memory(32,32)	339	1369	1945	2205



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Thank you for your attention!

