

# Lecture 10

# Introduction to CUDA

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#### Laborations

Lan 4-6 are ready, no changes planned *but* last minute changes may occur.

The "lab questions" are vital! Answers *must* be written down before we can examine you!

Thus - no lab reports needed.



#### **Lecture material**

Lecture material available on the web, new and last year's.

The old local course page is obsolete but is linked to

http://computer-graphics.se/TDDD56

The lecture material is linked from the "Lectures" page.



# **Previous lecture:**

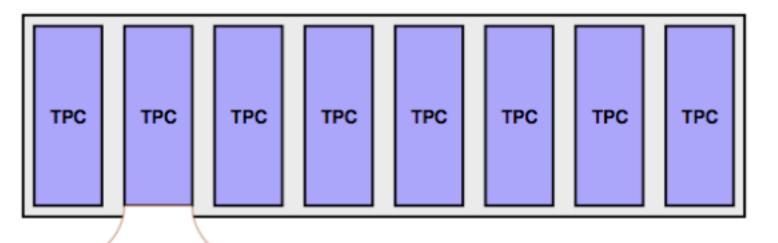
GPU development - why did it become a general purpose parallel architecture

**GPU** architecture

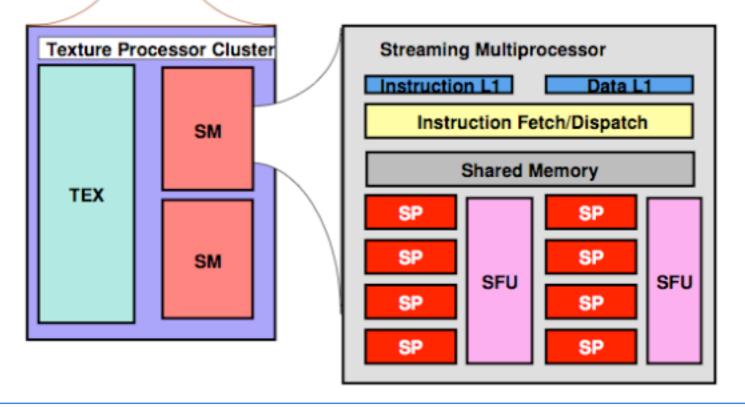
A quick look at GPU coding (Hello World!)



# **G80** processor hierarchy



8 top-level groups of TPCs



SM (Streaming Multiprocessor) is a group of 8 SIMD cores



# This lecture:

Programming model and language

Introduction to memory spaces and memory access

**Shared memory** 

Matrix multiplication example



# Lecture questions:

- 1. What concept in CUDA corresponds to a SM (streaming multiprocessor) in the architecture?
  - 2. How does matrix multiplication benefit from using shared memory?
    - 3. When do you typically need to synchronize threads?



# CUDA = Compute Unified Device Architecture

Really?

**Developed by NVidia** 



Designed to hide the graphics heritage and add control and flexibility



# Computing model:

- 1. Upload data to GPU
  - 2. Execute kernel
  - 3. Download result

Similar to shader-based solutions and OpenCL



# Integrated source

Source of host and kernel code in the same source file!

Major difference to shaders and OpenCL.

Kernel code identified by special modifiers.



#### **About CUDA**

**Architecture and C extension** 

Spawn a large number of threads, to be ran virtually in parallel

Just like in graphics! Fragments/computations not quite executed in parallel.

A bunch at a time - a warp.

Looks much more like an ordinary C program! No more "data stored as pixels" - just arrays!



# Simple CUDA example

A working, compilable example

```
#include <stdio.h>
                                             cudaMalloc( (void**)&cd, size );
                                             dim3 dimBlock( blocksize, 1 );
const int N = 16;
                                             dim3 dimGrid( 1, 1 );
const int blocksize = 16;
                                             simple<<<dimGrid, dimBlock>>>(cd);
                                             cudaMemcpy( c, cd, size, cudaMemcpyDeviceToHost );
__global__
                                             cudaFree( cd );
void simple(float *c)
                                             for (i = 0; i < N; i++)
                                              printf("%f ", c[i]);
c[threadIdx.x] = threadIdx.x;
                                             printf("\n");
                                             delete∏ c;
int main()
                                             printf("done\n");
                                             return EXIT_SUCCESS;
 int i;
float *c = new float[N];
float *cd;
 const int size = N*sizeof(float);
```



# Simple CUDA example

A working, compilable example

```
Allocate GPU memory
cudaMalloc( (void**)&cd, size );
dim3 dimBlock( blocksize, 1 );
                                 1 block, 16 threads
dim3 dimGrid( 1, 1 );
                                    Call kernel
simple<<<dimGrid, dimBlock>>>(cd);
cudaMemcpy( c, cd, size, cudaMemcpyDeviceToHost );
cudaFree( cd );
                                 Read back data
for (i = 0; i < N; i++)
 printf("%f ", c[i]);
printf("\n");
delete∏ c;
printf("done\n");
return EXIT_SUCCESS;
```



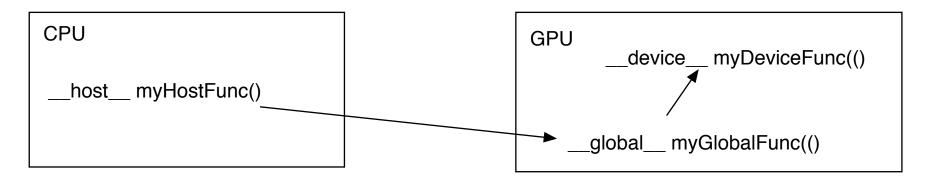
#### **Modifiers for code**

Three modifiers are provided to specify how code should be used:

\_\_global\_\_ executes on the GPU, invoked from the CPU. This is the entry point of the kernel.

\_\_device\_\_ is local to the GPU

\_\_host\_\_ is CPU code (superfluous).





# **Memory management**

cudaMalloc(ptr, datasize)
 cudaFree(ptr)

Similar to CPU memory management, but done by the CPU to allocate on the GPU

cudaMemCpy(dest, src, datasize, arg)

arg = cudaMemcpyDeviceToHost or cudaMemcpyHostToDevice



#### **Kernel execution**

simple<<<gri>dim, blockdim>>>(...)

grid = blocks, block = threads

**Built-in variables for kernel:** 

threadIdx and blockIdx blockDim and gridDim

(Note that no prefix is used, like GLSL does.)



# **Compiling Cuda**

nvcc

nvcc is nvidia's tool, /usr/local/cuda/bin/nvcc

Source files suffixed .cu

Command-line for the simple example:

nvcc simple.cu -o simple

(Command-line options exist for libraries etc)



# **Compiling Cuda for larger applications**

nvcc and gcc in co-operation

nvcc for .cu files

gcc for .c/.cpp etc

Mixing languages possible.

Final linking must include C++ runtime libs.

**Example: One C file, one CU file** 



# **Example of multi-unit compilation**

Source files: cudademokernel.cu and cudademo.c

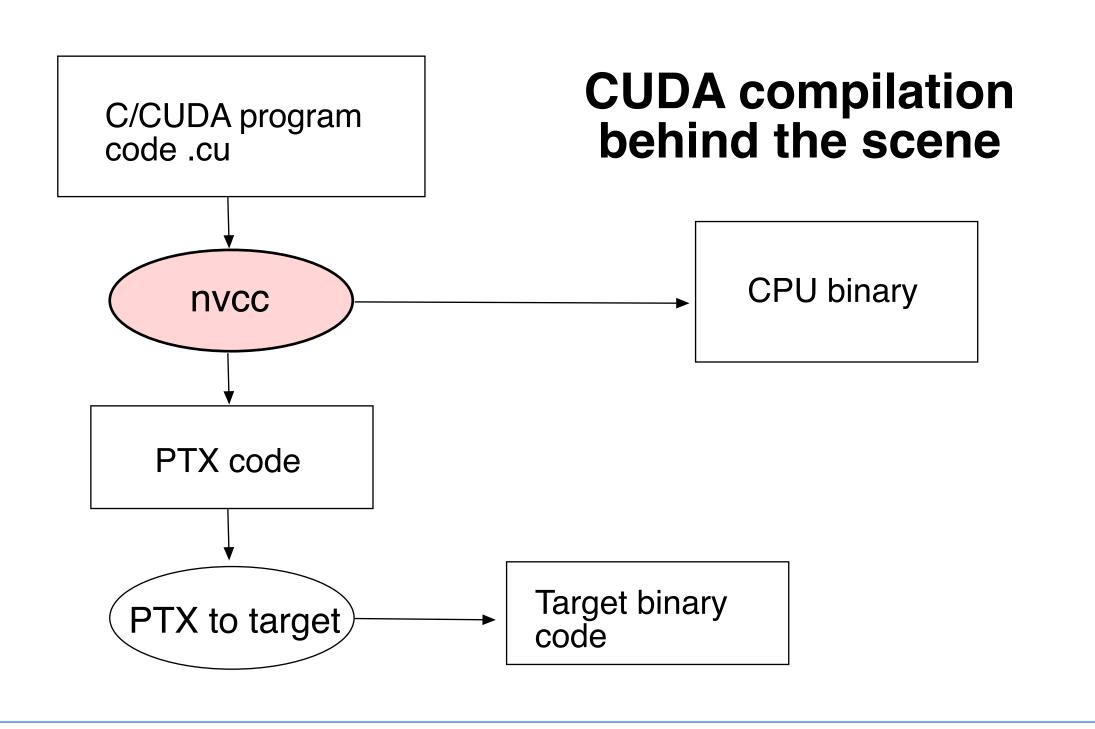
nvcc cudademokernel.cu -o cudademokernel.o -c

gcc -c cudademo.c -o cudademo.o -I/usr/local/cuda/include

g++ cudademo.o cudademokernel.o -o cudademo -L/usr/local/cuda/lib -lcuda -lcudart -lm

Link with g++ to include C++ runtime







# **Executing a Cuda program**

Must set environment variable to find Cuda runtime.

export DYLD\_LIBRARY\_PATH=/usr/local/cuda/lib:\$DYLD\_LIBRARY\_PATH

Then run as usual:

./simple

A problem when executing without a shell!

Launch with execve()



# **Computing with CUDA**

Organization and access

**Blocks**, threads...



# Warps

A warp is the minimum number of data items/threads that will actually be processed in parallel by a CUDA capable device. This number varies with different GPUs.

We usually don't care about warps but rather discuss threads and blocks.



# **Processing organization**

1 warp = 32 threads

1 kernel - 1 grid

1 grid - many blocks

1 block - 1 SM

1 block - many threads

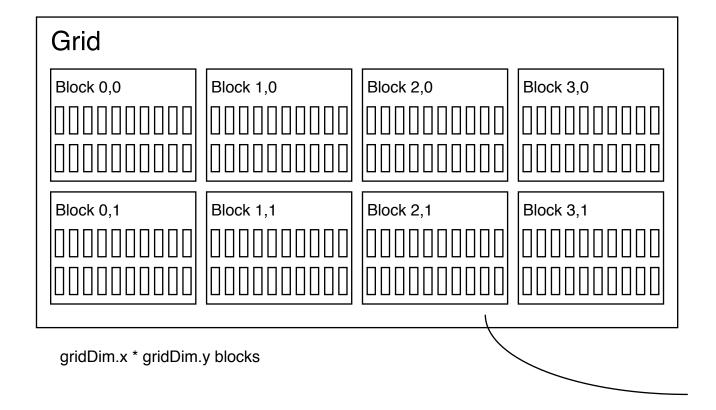
Use many threads and many blocks! > 200 blocks recommended.

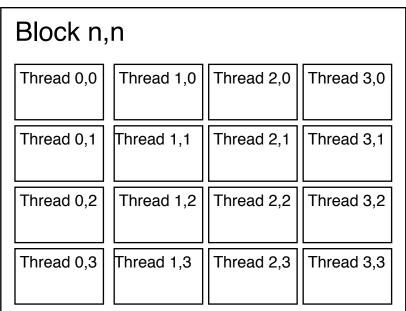
Thread # multiple of 32



# Distributing computing over threads and blocks

#### **Hierarcical model**





BlockDim.x \* blockDim.y threads



# Indexing data with thread/block IDs

Calculate index by blockldx, blockDim, threadldx

Another simple example, calculate square of every element, device part:

```
// Kernel that executes on the CUDA device
__global__ void square_array(float *a, int N)
{
  int idx = blockIdx.x * blockDim.x + threadIdx.x;
  if (idx<N) a[idx] = a[idx] * a[idx];
}</pre>
```



# Host part of square example

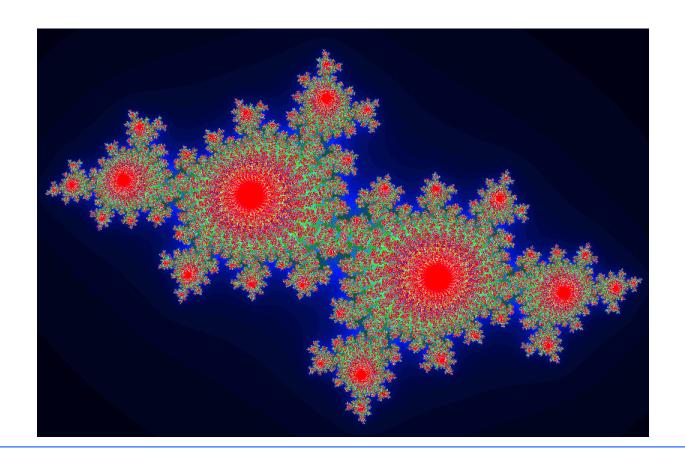
#### Set block size and grid size

```
// main routine that executes on the host
int main(int argc, char *argv[])
 float *a_h, *a_d; // Pointer to host and device arrays
 const int N = 10; // Number of elements in arrays
 size_t size = N * sizeof(float);
 a_h = (float *)malloc(size);
 cudaMalloc((void **) &a_d, size); // Allocate array on device
// Initialize host array and copy it to CUDA device
 for (int i=0; i<N; i++) a_h[i] = (float)i;
 cudaMemcpy(a_d, a_h, size, cudaMemcpyHostToDevice);
// Do calculation on device:
 int block_size = 4;
 int n_blocks = N/block_size + (N%block_size == 0 ? 0:1);
 square_array <<< n_blocks, block_size >>> (a_d, N);
// Retrieve result from device and store it in host array
 cudaMemcpy(a_h, a_d, sizeof(float)*N, cudaMemcpyDeviceToHost);
// Print results and cleanup
 for (int i=0; i<N; i++) printf("%d %f\n", i, a_h[i]);
 free(a_h); cudaFree(a_d);
```



# Julia example

- Bigger problem, addressing calculation must be 2D
  - Simple OpenGL output (similar to the labs)





# Julia example

```
For this case: Separate for x and y
                       __global__ void kernel( unsigned char *ptr, float r, float im)
                           // map from blockIdx to pixel position
                           int x = blockIdx.x * blockDim.x + threadIdx.x;
                           int y = blockIdx.y * blockDim.y + threadIdx.y;
                           int offset = x + y * DIM;
                           // now calculate the value at that position
                           int juliaValue = julia( x, y, r, im );
Actual index
which implies
                        --- calculate colors ---
                           ptr[offset*4 + 0] = red;
memory position
                           ptr[offset*4 + 0] = green;
                           ptr[offset*4 + 0] = blue;
                           ptr[offset*4 + 3] = 255;
```

#### **Every thread computes one single pixel!**



# Julia conclusions

Many blocks, many treads in each block. Make sure everything is in use.

Index by thread and block.

Exceptional speedup - trivially parallizable problem!

Load balancing? No problem. Why?



# Conclusion about indexing

Every thread does its own calculation for indexing memory!

blockldx, blockDim, threadldx

1, 2 or 3 dimensions

**Usually 2 dimensions** 



# Memory access

Vital for performance!

**Memory types** 

Coalescing

**Example of using shared memory** 



# **Memory types**

Global

**Shared** 

**Constant (read only)** 

**Texture cache (read only)** 

Local

Registers

Care about these when optimizing - not to begin with



# **Global memory**

400-600 cycles latency!

Shared memory fast temporary storage

Coalesce memory access!

Continuous
Aligned on power of 2 boundary
Addressing follows thread numbering

Use shared memory for reorganizing data for coalescing!



# Using shared memory to reduce number of global memory accesses

Read blocks of data to shared memory

**Process** 

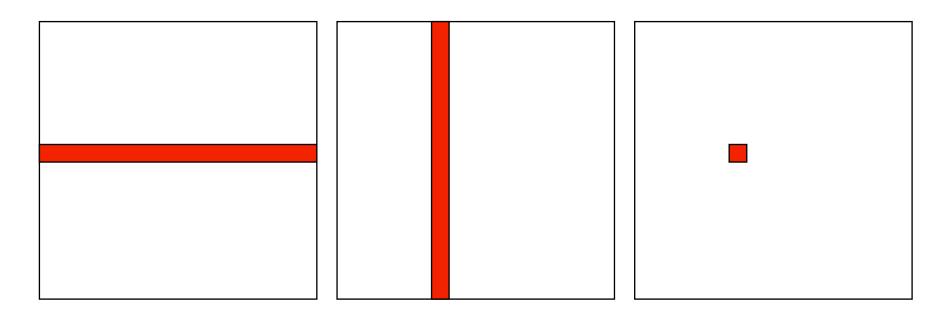
Write back as needed

Shared memory as "manual cache"

**Example: Matrix multiplication** 



#### **Matrix multiplication**



To multiply two N\*N matrices, every item will have to be accessed N times!

Naive implementation: 2N<sup>3</sup> global memory accesses!



# Matrix multiplication on CPU

#### Simple triple "for" loop

```
void MatrixMultCPU(float *a, float *b, float *c, int theSize)
{
  int sum, i, j, k;

// For every destination element
  for(i = 0; i < theSize; i++)
    for(j = 0; j < theSize; j++)
    {
      sum = 0;
      // Sum along a row in a and a column in b
      for(k = 0; k < theSize; k++)
        sum = sum + (a[i*theSize + k]*b[k*theSize + j]);
      c[i*theSize + j] = sum;
    }
}</pre>
```



#### **Naive GPU version**

#### Replace outer loops by thread indices

```
__global__ void MatrixMultNaive(float *a, float *b, float *c, int
theSize)
{
  int sum, i, j, k;

  i = blockIdx.x * blockDim.x + threadIdx.x;
  j = blockIdx.y * blockDim.y + threadIdx.y;

// For every destination element
  sum = 0;

// Sum along a row in a and a column in b
  for(k = 0; k < theSize; k++)
    sum = sum + (a[i*theSize + k]*b[k*theSize + j]);
  c[i*theSize + j] = sum;
}</pre>
```



#### Naive GPU version inefficient

Every thread makes 2N global memory accesses!

Can be significantly reduced using shared memory



# **Optimized GPU version**

Data split into blocks.

Every element takes part in all the blocks in the same row for A, column for B

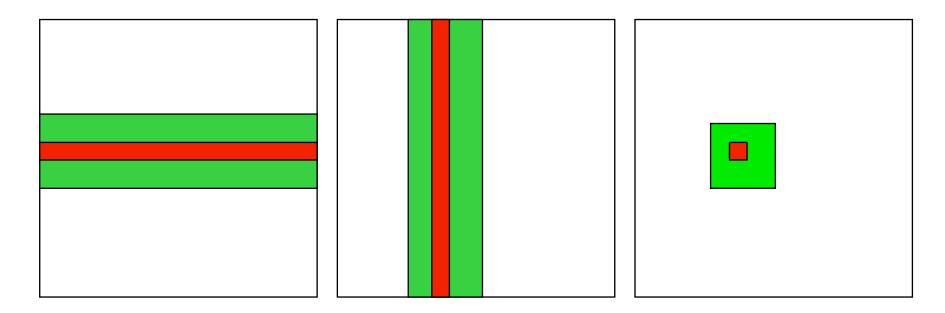
For every such block

Every thread reads one element to shared memory

Then loop over the appropriate row and column for the block



#### Contributing areas for patch



Let each block handle a part of the output (green right).

Green areas middle and left contibute to output.

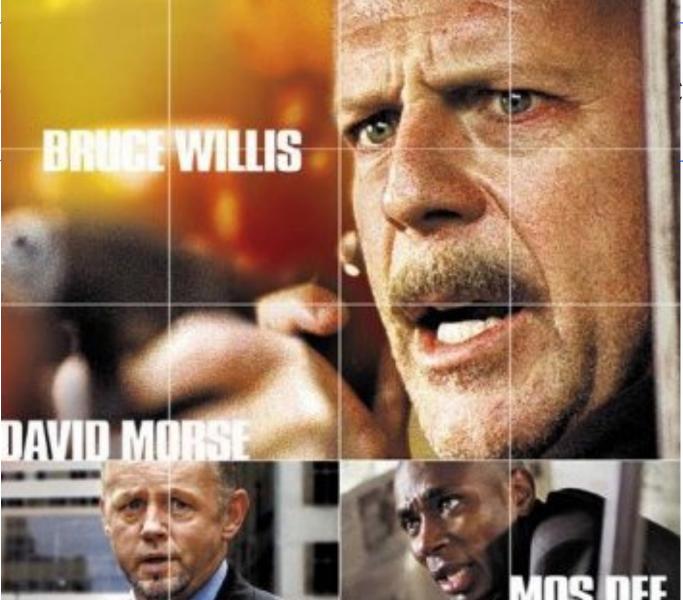
Load the contributing areas into shared memory.



# Example: 16 blocks



Info



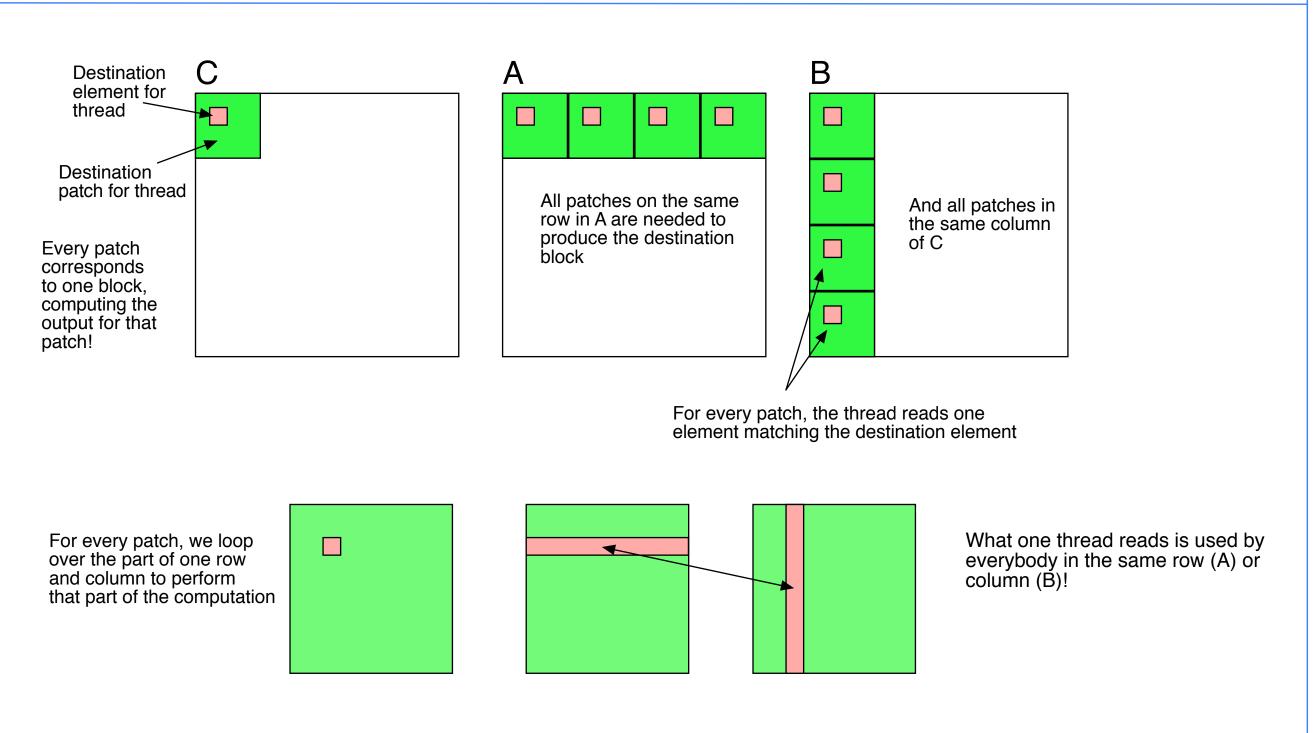
s, ISY, LiTH

# FILM BY RICHARD DONNER BLOCKS

DVD

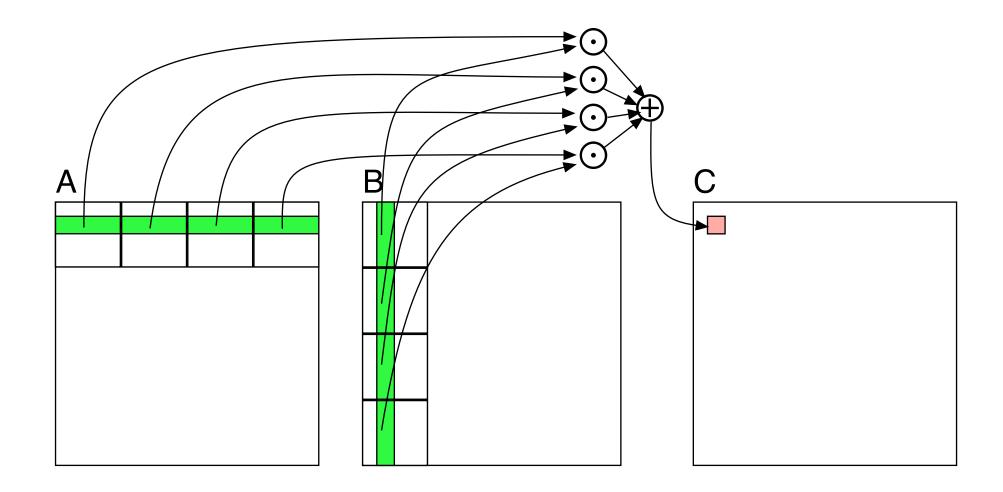
16ブロック







## Piece by piece, patch by patch





# Optimized GPU version

Loop over patches (1D)

Allocate shared memory

Copy one element to shared memory

Loop over row/column in patch, compute, accumulate result for one element

Write result to global memory

```
__global__ void MatrixMultOptimized( float* A, float* B, float* C, int theSize)
int i, j, k, b, ii, jj;
// Global index for thread
i = blockIdx.x * blockDim.x + threadIdx.x;
j = blockIdx.y * blockDim.y + threadIdx.y;
float sum = 0.0;
// for all source patches
for (b = 0; b < gridDim.x; b++)
 __shared__ float As[BLOCKSIZE*BLOCKSIZE];
 __shared__ float Bs[BLOCKSIZE*BLOCKSIZE];
 // Index locked to patch
 ii = b * blockDim.x + threadIdx.x;
 jj = b * blockDim.y + threadIdx.y;
 As[threadIdx.y*blockDim.x + threadIdx.x] = A[ii*theSize + j];
 Bs[threadIdx.y*blockDim.x + threadIdx.x] = B[i*theSize + jj];
 __syncthreads(); // Synchronize to make sure all data is loaded
 // Loop, perform computations in patch
 for (k = 0; k < blockDim.x; ++k)
  sum += As[threadIdx.y*blockDim.x + k]
  * Bs[k*blockDim.x + threadIdx.x];
 __syncthreads(); // Synch so nobody starts next pass prematurely
C[i*theSize + j] = sum;
```



#### 5-10 times faster? So what did I do?

- Decent number of threads and blocks
- Use shared memory for temporary storage
- All threads read ONE item, but use many!
  - Synchronize
- Even more for CPU compared to single-thread CPU :)



# Modified computing model:

Upload data to global GPU memory

For a number of parts, do:

Upload partial data to shared memory

**Process partial data** 

Write partial data to global memory

Download result to host



## **Synchronization**

As soon as you do something where one part of a computation depends on a result from another thread, you must synchronize!

\_\_syncthreads()

**Typical implementation:** 

- Read to shared memory
  - \_\_syncthreads()
- Process shared memory
  - \_\_synchthreads()
- Write result to global memory



## **Synchronization**

Really wonderfully simple - everybody are doing the same thing anyway!

Synchronization simply means "wait until everybody are done with this part"

Deadlocks can still occur!



# Limitation of synchronization

Synchronization can only be done within a block!
No synchronization between blocks!

Why is this a necessary limitation?



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Synchronization can only be done within a block!
No synchronization between blocks!

Why is this a necessary limitation?

Because all blocks are not active at the same time!

Blocks are queued until an SM is free!



# Limitation of synchronization

Synchronization can only be done within a block!
No synchronization between blocks!

Why is this a necessary limitation?

Because all blocks are not active at the same time!

Blocks are queued until an SM is free!

But I must synchronize globally!

**Answer: Run multiple kernels! More on this later.** 



# Lecture questions revisited:

- 1. What concept in CUDA corresponds to a SM (streaming multiprocessor) in the architecture?
  - 2. How does matrix multiplication benefit from using shared memory?
    - 3. When do you typically need to synchronize threads?



#### **Summary:**

- Make threads and blocks to make the hardware occupied
  - Access data depending on thread/block number
    - Memory accesses are expensive!
      - Shared memory is fast
    - Make threads within a block cooperate
      - Synchronize



#### That's all folks!

Next: More about memory management and optimization.