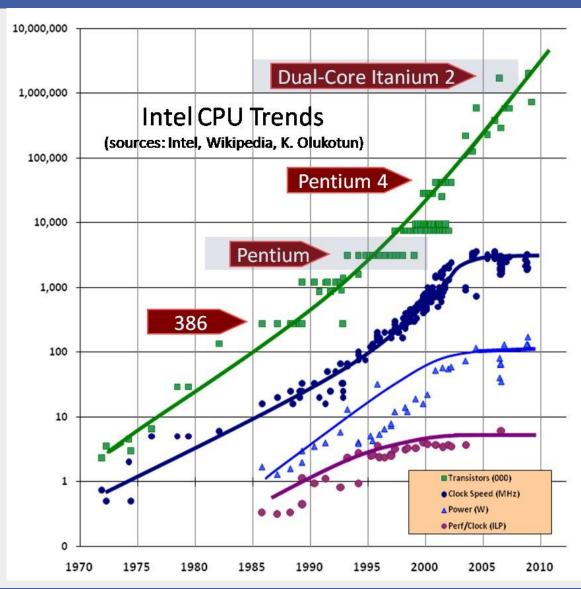


: ITMO UNIVERSITY

Parallel Programming with CUDA. Basics

Katerina Bolgova, PhD eScience Research Institute & HPC Department

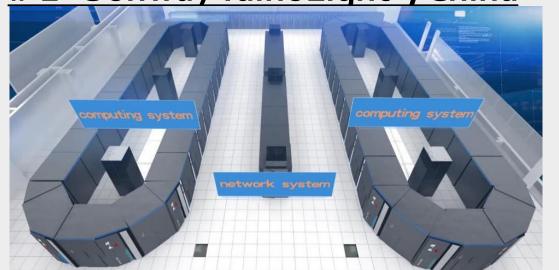
What is this picture about?





Top 500 supercomputers (November, 2017):

1 "Sunway TaihuLight", China



Total Cores	Power (kW)	
10,649,600	15,371.00	

Rmax (TFlops)	Rpeak (TFlops)
93,014.6	125,435.9

#227 "Lomonosov", Russia

Total Cores	Power (kW)
78 , 660	2,800.00

Rmax (TFlops)	Rpeak (TFlops)
901.9	1,700.2



2.3 PFlops



7.0 Megawatts

7000 homes



7.0 Megawatts

Traditional CPUs are not economically feasible

Moore's law isn't true any longer: It's impossible to make reliable lowcost processors that run significantly faster







Parallel Computing / Memory Architectures

Distributed Memory

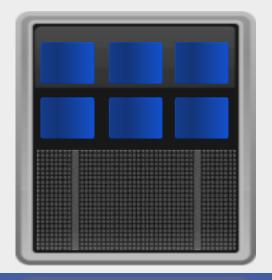
Shared Memory

Hybrid Shared-Distributed Memory

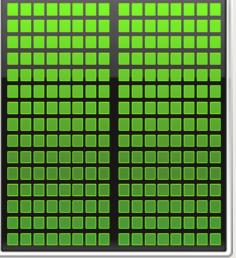
And

heterogeneous computing

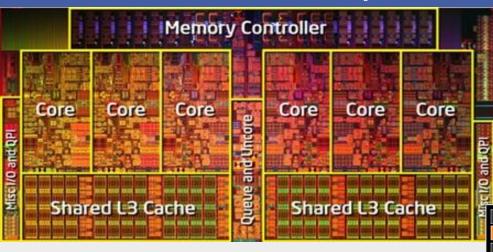
CPU



GPU

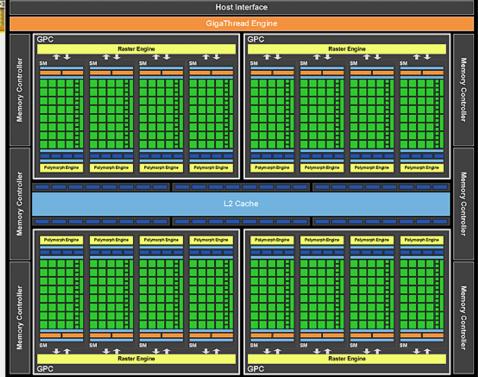






Intel Core i7

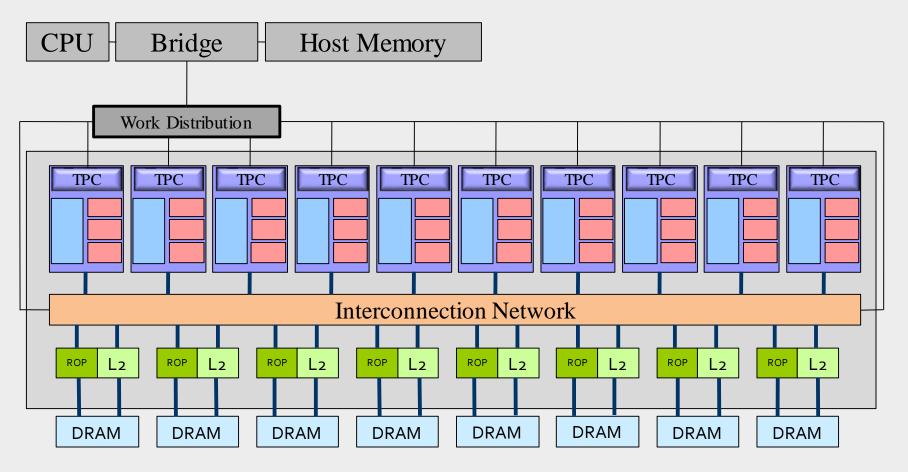
Fermi





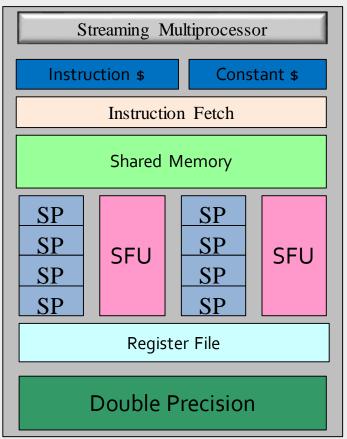
Introduction

NVIDIA history: http://www.nvidia.ru/object/corporate-timeline-ru.html Tesla 10 Architecture

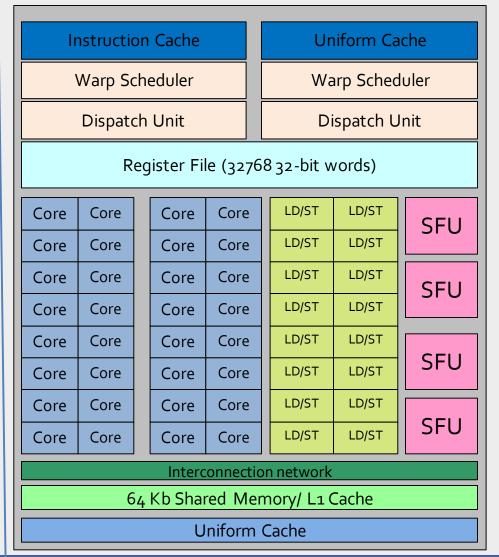


Introduction

Tesla 10 Architecture (Streaming multiprocessor, SM)



Tesla 20 Architecture (SM)

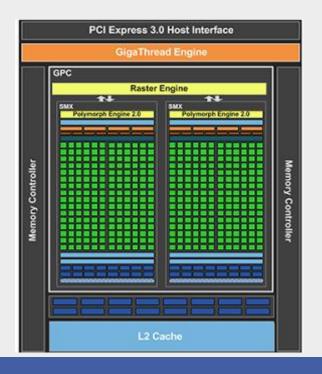




Introduction

NVIDIA accelerators:

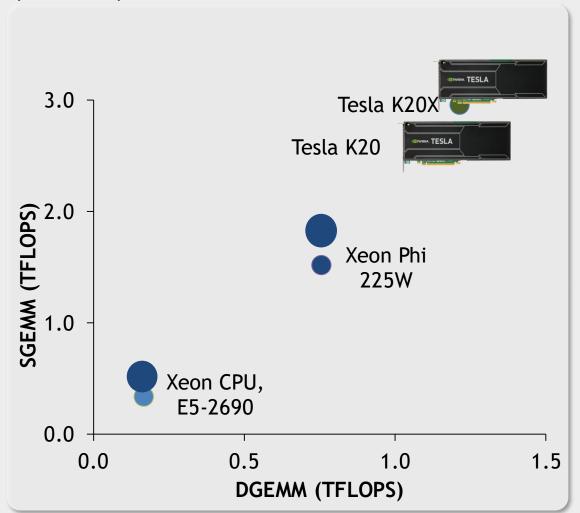
- Fermi
- Kepler
- Maxwell
- Pascal
- Volta





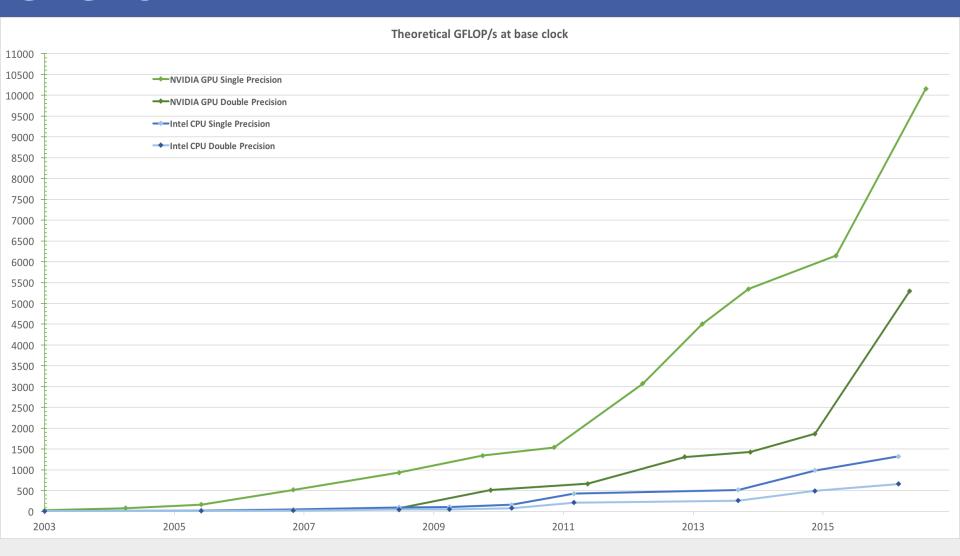
CPU vs. GPU

Here was a video. You can find it by link: https://www.youtube.com/watch?v=-P28LKWTzrl



Tesla K20X vs Xeon CPU 8x Faster SGEMM 6x Faster DGEMM Tesla K20X vs Xeon Phi 90% Faster SGEMM 60% Faster DGEMM

GPGPU



* CUDA C Programming Guide

1/6/2020



GPGPU

General-Purpose computing on Graphics Processing Units:

 became practical and popular after 2001, with the advent of both programmable shaders and floating point support on graphics processors

Most popular implementations:

- OpenCL
- DirectCompute
- CUDA



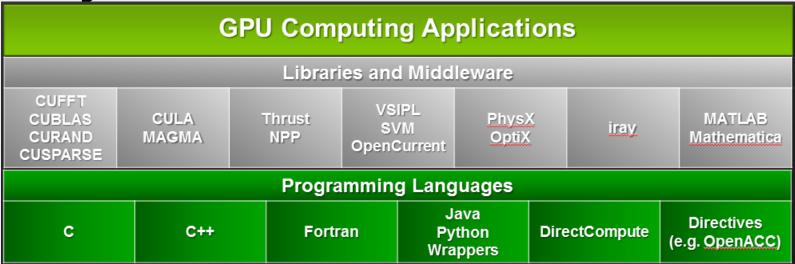
Compute Unified Device Architecture

CUDA® - a General-Purpose Parallel Computing Platform and Programming Model:

was introduced by NVIDIA in 2006

1/6/2020

- expose GPU computing for general purpose
- is designed to support various languages and application programming interfaces



 CUDA C/C++ - Small set of extensions to enable heterogeneous programming



Compute Unified Device Architecture

Programming Approaches

Libraries

"Drop-in"
Acceleration

OpenACC Directives

Easily Accelerate Apps

Programming Languages

Maximum Flexibility

Development Environment



Nsight IDE
Linux, Mac and Windows
GPU Debugging and
Profiling

CUDA-GDB debugger NVIDIA Visual Profiler

Open Compiler Tool Chain



Enables compiling new languages to CUDA platform, and CUDA languages to other architectures

Hardware Capabilities

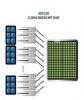


SMX

Dynamic Parallelism



HyperQ



GPUDirect





Compute Unified Device Architecture

The CUDA Toolkit:

- is free
- available at https://developer.nvidia.com
- includes a compiler, math libraries and tools for debugging and optimizing the performance of applications

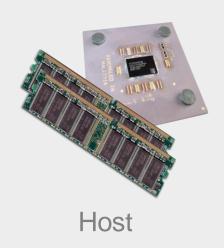
There are a lot of code samples, programming guides, user manuals, API references and other documentation. Most useful of them:

- CUDA Programming Guide, http://docs.nvidia.com/cuda/cuda-c-programming-guide/
- CUDA C Best Practices Guide,
 http://docs.nvidia.com/cuda/cuda-c-best-practices-guide



Heterogeneous Computing

- Terminology:
 - Host The CPU and its memory (host memory)
 - Device The GPU and its memory (device memory)





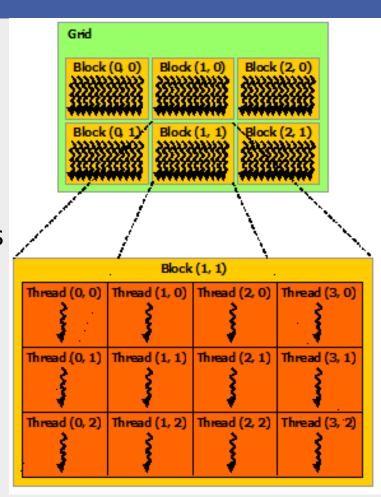
Device

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CUDA. Programming Model

Basic concepts:

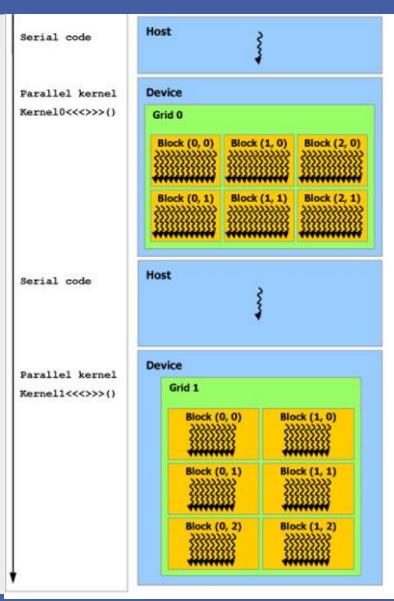
- Host: The CPU and its memory (host memory). Serial code is executed here.
- *Device:* The GPU and its memory (device memory). Parallel code is executed here.
- *Kernel*: function that is executed N times in parallel
- kernels are executed by N different CUDA threads. Each thread has its own unique ID (treadIdx)
- Threads form a 1/2/3-dimensional **block**
- Blocks are organized into 1/2/3dimensional grid





CUDA. Programming Model

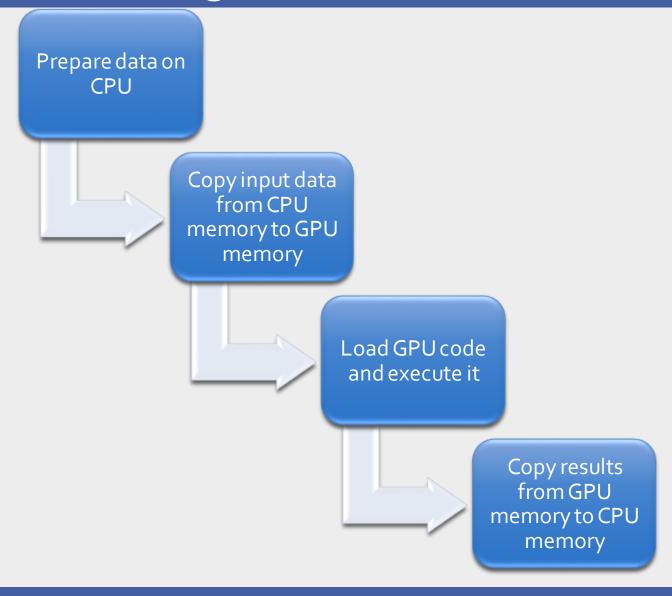
- Thread blocks are required to execute independently: It must be possible to execute them in any order, in parallel or in series
- There is a limit to the number of threads per block
- Threads within a block can cooperate by sharing data
- Kernel=grid



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Simple Processing Flow





"Hello world" with GPU

- CUDA C/C++ keyword __global__ indicates a function that runs on the device.
- Triple angle brackets (mykernel<<<1,1>>>()) mark a call from host code to device code (also called a "kernel launch").
- *nvcc* separates source code into host and device components:
 - Device functions (e.g. mykernel()) processed by NVIDIA compiler
 - Host functions (e.g. main()) processed by standard host compiler (gcc, cl.exe)

That's 'minimum' that needs to execute a function on the GPU



CUDA runtime API. Basics

- The Compute Capability describes the features supported by a CUDA hardware.
- Build-in structure cudaDeviceProp contains all information about device Compute Capabitity

GPU	Compute Capability
GeForce GTX 980 M	5.2
GeForce GTX 770	5.0
Tesla K40	3.5
Tesla C2050/C2070	2.0
GeForce GTX 48oM	2.0
GeForce 8800 GT	1.1
GeForce 8800 GTX	1.0

CUDA runtime API. Basics

```
int main ( int argc, char * argv [] )
   int
                deviceCount;
   cudaDeviceProp devProp;
   cudaGetDeviceCount ( &deviceCount );
                      ( "Found %d devices\n", deviceCount );
   printf
   for ( int device = 0; device < deviceCount; device++ )</pre>
      cudaGetDeviceProperties ( &devProp, device );
     printf ( "Device %d\n", device );
      printf ( "Compute capability
                                      : %d.%d\n", devProp.major, devProp.minor);
     printf ( "Name
                                       : %s\n", devProp.name);
     printf ( "Total Global Memory : %d\n", devProp.totalGlobalMem );
      printf ( "Shared memory per block: %d\n", devProp.sharedMemPerBlock );
      printf ( "Registers per block
                                      : %d\n", devProp.regsPerBlock);
      printf ( "Warp size
                                      : %d\n", devProp.warpSize);
     printf ( "Max threads per block : %d\n", devProp.maxThreadsPerBlock );
      printf ( "Total constant memory : %d\n", devProp.totalConstMem );
     printf ( "Multiprocessor Count : %d\n", devProp.devProp.mrltiProcessorCount);
   return 0;
```

CUDA C/C++

- It consists of a minimal set of extensions to the C language and a runtime library.
- Extensions allow programmers to define a kernel as a C function and use some new syntax to specify the grid and block dimension each time the function is called:
 - Function Type Qualifiers
 - Variable Type Qualifiers
 - Built-in Vector Types
 - Built-in Variables



CUDA C. Function Type Qualifiers

Qualifier	Executed at	Called from
device	device	device
global	device	host
host	host	host

- The <u>__global</u>__ qualifier declares a function as being a kernel.
- __global__ functions must have void return type
- A call to a __global__ function is asynchronous
- The <u>__device__</u> and <u>__host__</u> qualifiers can be used together however, in which case the function is compiled for both the host and the device.
- The <u>__global</u>_ and <u>__host</u>_ qualifiers cannot be used together
- It is equivalent to declare a function with only the __host__ qualifier or to declare it without any of qualifiers



CUDA C. Built-in Vector Types

- Vector types are derived from the basic integer and floating-point types:
 - (u) char, (u) int, (u) short, (u) long, float could have 1-/
 2-/3-/4-dimensions
 - longlong, double could have 1-/2-dimensions
 - the 1st, 2nd, 3rd, and 4th components are accessible through the fields x,
 y, z, and w, respectively
- They all come with a constructor function: make_<type name>

Example:

```
float4 b = make_float4 ( 1, 2, 5, 3 );
```

 The type dim3 is an integer vector type based on uint3 that is used to specify dimensions. When defining a variable of type dim3, any component left unspecified is initialized to 1.



CUDA C. Built-in Variables

Built-in variables specify the grid and block dimensions and the block and thread indices. They are only valid within functions that are executed on the device

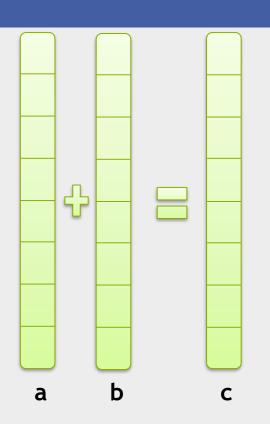
- dim3 gridDim contains the dimensions of the grid,
- uint3 **blockIdx** contains the block index within the grid,
- dim3 blockDim contains the dimensions of the block,
- uint3 threadIdx contains the thread index within the block,

CUDA C/C++ Programming

Simple Example: vector addition

- $C_i = a_i + b_i$
- But before let's start by adding two integers :

- Note: that we use pointers for the variables
- add() runs on the device, so a, b and c must point to device memory
- We need to allocate memory on the GPU



Memory Management

- Host and device memory are separate entities
 - Device pointers point to GPU memory
 - May be passed to/from host code
 - May not be dereferenced in host code
 - Host pointers point to CPU memory
 - May be passed to/from device code
 - May not be dereferenced in device code



- Simple CUDA API for handling device memory
 - cudaMalloc(), cudaFree(), cudaMemcpy()
 - Similar to the C equivalents malloc(), free(), memcpy()



Memory Management

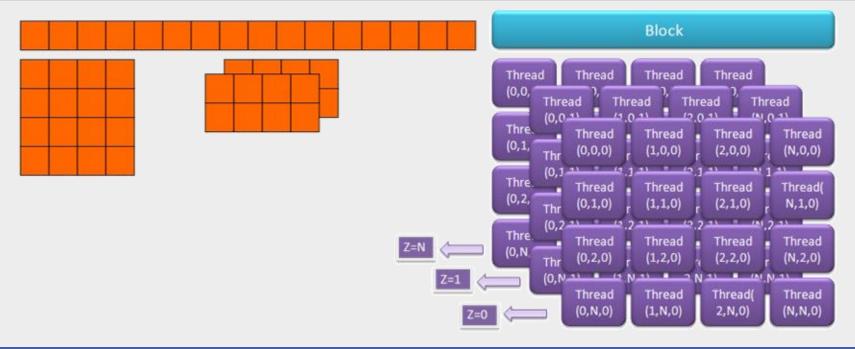
```
( void ** devPtr, size t size );
cudaError t cudaMalloc
                           ( void * devPtr );
cudaError t cudaFree
                            ( void * dst, const void * src,
cudaError t cudaMemcpy
                            size t count, enum cudaMemcpyKind kind );
cudaError t cudaMemcpyAsync ( void * dst, const void * src,
                              size t count,
                              enum cudaMemcpyKind kind,
                              cudaStream t stream );
                            ( void * dst, int value, size t count );
cudaError t cudaMemset
cudaError t cudaMallocHost ( void ** devPtr, size t size );
```

CUDA C/C++ Programming

```
int main() {
                int a, b, c;
int *d a, *d b, *d c;
// host copies of a, b, c
// device copies of a, b, c
                int size = sizeof(int);
        // Allocate space for device copies of a, b, c
                cudaMalloc((void **)&d a, size);
                cudaMalloc((void **)&d b, size);
                cudaMalloc((void **)&d c, size);
        // Setup input values
                a = 2;
               b = 7;
        // Copy inputs to device
                cudaMemcpy(d a, &a, size, cudaMemcpyHostToDevice);
                cudaMemcpy(d b, &b, size, cudaMemcpyHostToDevice);
        // Launch add() kernel on GPU
                add<<<1,1>>> (d a, d b, d c);
        // Copy result back to host
                cudaMemcpy(&c, d c, size, cudaMemcpyDeviceToHost);
        // Cleanup
                cudaFree(d a); cudaFree(d b); cudaFree(d c);
                return 0;
```

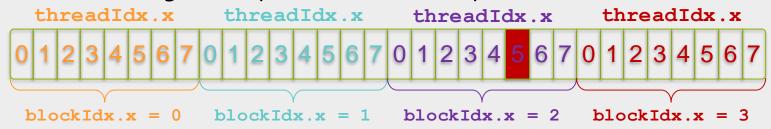
CUDA C/C++. Kernel Launch

```
Kernel_name<<<grid, block, mem, stream>>>( params ),
Where:
  - dim3 grid - grid size (number of block);
  - dim3 block - block size (thread number per block).
  - size_t mem - amount of shared memory per block;
  - cudaStream_t stream - CUDA stream number.
```



CUDA C. Indexing Arrays with Blocks and Threads

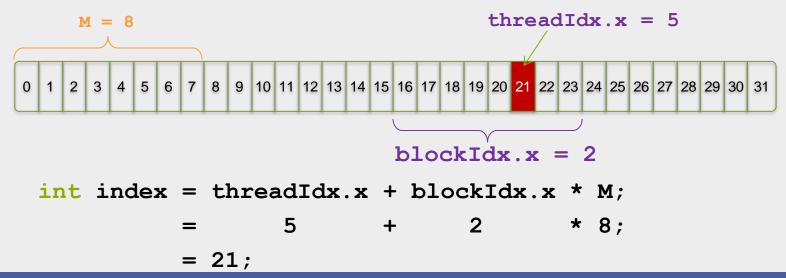
Consider indexing an array with one element per thread (8 threads/block)



With M threads/block a unique index for each thread is given by:

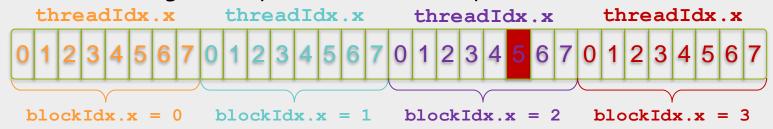
```
int index = threadIdx.x + blockIdx.x * M;
```

Which thread will operate on the red element?



CUDA C. Indexing Arrays with Blocks and Threads

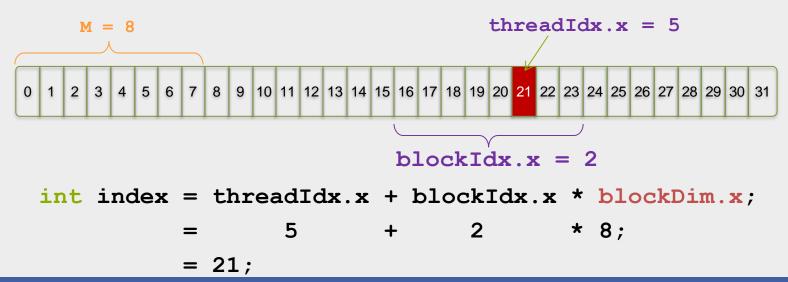
Consider indexing an array with one element per thread (8 threads/block)



With M threads/block a unique index for each thread is given by:

```
int index = threadIdx.x + blockIdx.x * blockDim.x;
```

Which thread will operate on the red element?



CUDA C. Vector Addition

```
<u>global</u> void vector_add(float *a, float *b, float *c)
       int index = blockIdx.x * blockDim.x + threadIdx.x;
       c[index] = a[index] + b[index];
int main() {
       // Kernel invocation with one block of N * N * 1 threads
       int numBlocks = 1;
       dim3 threadsPerBlock(N, N);
       vector_add<<<numBlocks, threadsPerBlock>>>(A, B, C);
```

CUDA runtime API. Time Measurement

Event in CUDA is **cudaEvent_t** object that is used for indicate "the point" of some event. It's used for event management.

```
cudaError_t cudaEventCreate ( cudaEvent_t * );
cudaError_t cudaEventRecord ( cudaEvent_t *, cudaStream_t );
cudaError_t cudaEventQuery ( cudaEvent_t );
cudaError_t cudaEventSynchronize ( cudaEvent_t );
cudaError_t cudeEventElapsedTime ( float * time, cudaEvent_t st, cudaEvent_t sp );
cudaError_t cudaEventDestroy ( cudaEvent_t );
```

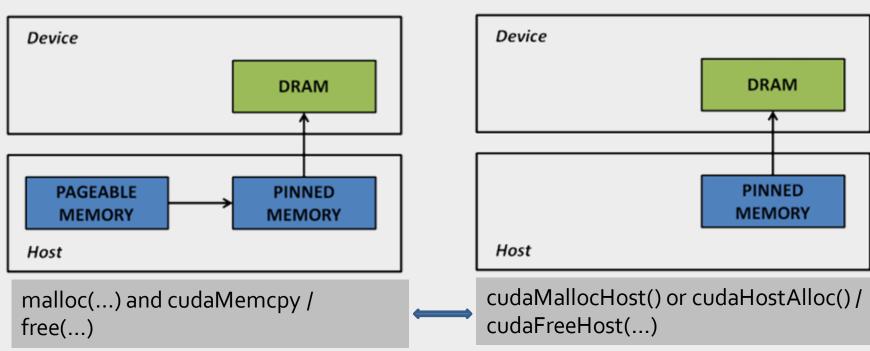
CUDA C. Vector Addition

```
int main() {
      cudaEvent t start, stop;
      cudaEventCreate(&start);
      cudaEventCreate(&stop);
      float qpuTime;
      cudaEventRecord ( start, 0 );
      vector add<<<numBlocks, threadsPerBlock>>>(A, B, C);
      cudaEventRecord ( stop, 0);
      cudaEventSynchronize (stop) ;
      cudaEventElapsedTime (&gpuTime, start, stop );
      printf("time spent executing by the GPU: %.2f
                           millseconds\n", qpuTime );
      cudaEventDestroy (start);
      cudaEventDestroy (stop);
```

CUDA C. Pinned-memory

PAGEABLE DATA TRANSFER

- Host (CPU) data allocations are pageable by default.
- the CUDA driver must first allocate a temporary page-locked, or "pinned", host array, copy the host data to the pinned array, and then transfer the data from the pinned array to device memory



* How to Optimize Data Transfers in CUDA C/C++:

https://devblogs.nvidia.com/parallelforall/how-optimize-data-transfers-cuda-cc/

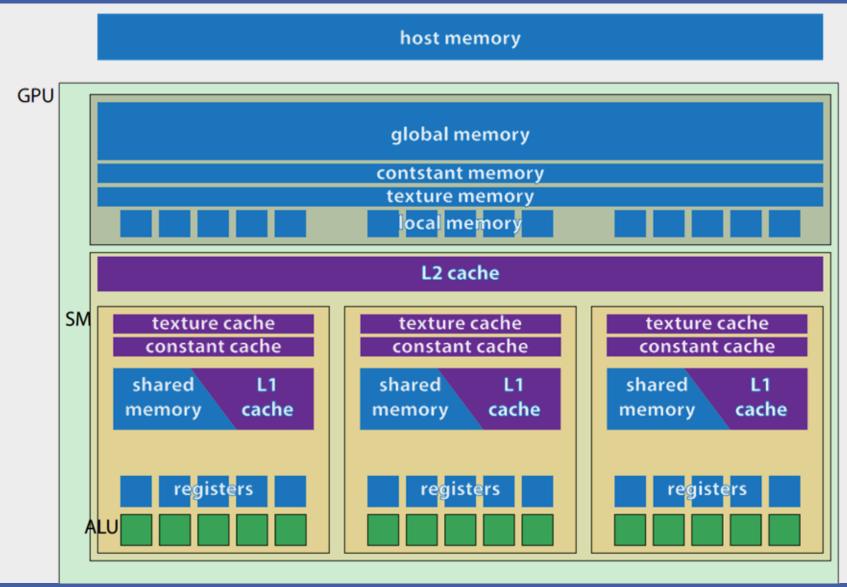


PINNED DATA TRANSFER

CUDA. Memory Hierarchy

Memory Type	Access	Level	Speed	Localization
Registers	R/W	Per-thread	High	SM
Local	R/W	Per-thread	Low	DRAM
Shared	R/W	Per-block	High	SM
Global	R/W	Per-grid	Low	DRAM
Constant	R/O	Per-grid	High	DRAM
Texture	R/O	Per-grid	High	DRAM

CUDA. Memory Hierarchy





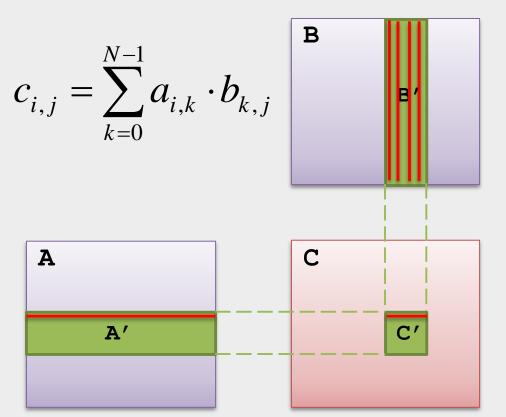
39

CUDA. Memory Hierarchy

Memory Type	Access	Level	Speed	Localization
Registers	R/W	Per-thread	High	SM
Local	R/W	Per-thread	Low	DRAM
Shared	R/W	Per-block	High	SM
Global	R/W	Per-grid	Low	DRAM
Constant	R/O	Per-grid	High	DRAM
Texture	R/O	Per-grid	High	DRAM

Sample. Matrix Multiplication

- Consider 2 matrices A и B with (N*N) size
- Each block calculates a part of result matrix C
- Each thread in block calculates
 1 element in this part
- To simplify:
 - N = 2048
 - Block_size = 32
 - Each matrix is 1D array



Matrix Multiplication. Kernel

```
#define BLOCK SIZE 32
#define N 2048
global void matMult ( float * a, float * b, int n,
float * c )
      int bx = blockIdx.x;
      int by = blockIdx.y;
      int tx = threadIdx.x;
      int ty = threadIdx.y;
      float sum = 0.0f;
      int ia = n * BLOCK SIZE * by + n * ty;
      int ib = BLOCK SIZE * bx + tx;
      int ic = ia + ib;
      for (int k = 0; k < n; k++)
            sum += a[ia + k] * b[ib + k*n];
      c[ic] = sum;
```

Matrix Multiplication. Main ()

```
int numBytes = N * N * sizeof(float); //define memory size
// allocate host memory
      float * h A = (float*)malloc(N * N * sizeof(float));;
      float * h B = (float*)malloc(N * N * sizeof(float));;
      float * h C = (float*)malloc(N * N * sizeof(float));;
/*init matrix*/ ...
//assign variable for device
      float * d A; float * d B; float * d C;
// allocate device memory
      cudaMalloc((void**)&d A, numBytes);
      cudaMalloc((void**)&d B, numBytes);
      cudaMalloc((void**)&d C, numBytes);
// set kernel launch configuration
      dim3 threads (BLOCK SIZE, BLOCK SIZE);
      dim3 blocks(N / BLOCK SIZE, N / BLOCK SIZE);
/*...*/
//copy data from host to device
      cudaMemcpy(d A, h A, numBytes, cudaMemcpyHostToDevice);
      cudaMemcpy(d B, h B, numBytes, cudaMemcpyHostToDevice);
```

Matrix Multiplication. Main ()

```
//kernel launch
      matMult Global mem<<<<blooks, threads>>> (d A, d B, N, d C);
//copy data from device to host
       cudaMemcpy(h C, d C, numBytes, cudaMemcpyDeviceToHost);
/*...*/
//memory free
       cudaFree (d A);
       cudaFree(d B);
       cudaFree(d C);
       free(h A);
       free(h B);
       free(h C);
       return 0;
```

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Matrix Multiplication. Global memory

Sequential code:

• CPU: Intel Core i7 58-20K 3,3 GHz

Dram: 16 GB

GPU code:

Name :GeForce GTX 960

Compute capability: 5.2

	Execution Time	Rate
Sequential code	69773,2	-
Global Memory	3230	21,6



• <u>BUT</u>:

- Each element (thread)
 - 2*N arithmetic operations
 - 2*N accesses to global memory
- Global Memory has a low access speed (200-400 clock cycles)



CUDA. Shared memory

- is much faster than global memory
- is allocated per thread block, so all threads in the block have access to the same shared memory.
- Threads can access data in shared memory loaded from global memory by other threads within the same thread block
- When sharing data between threads, we need to be careful to avoid race conditions

```
__shared__ int dSt[32];
__shared__ float dSum;

extern __shared__ int dDyn[];
```

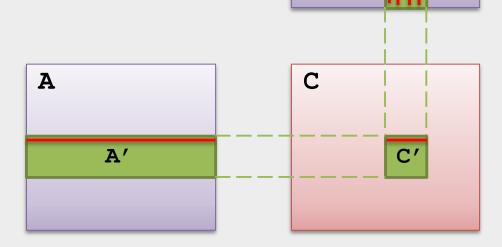
Usage pattern

```
/*Load data from Global memory*/
__syncthreads()
/* some calculations */
__syncthreads()
/* write result to global memory */
```



Matrix Multiplication

- During the calculation of the matrix C' is constantly used the same elements from matrices A and B
 - Repeatedly read from the global memory
- These reusable elements form stripes in the matrices A and B
- The size of this strip is N*32 and even one such strip is not placed in the shared-memory



B

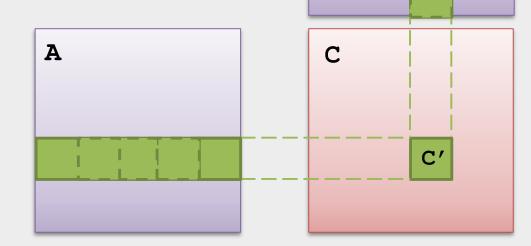
32*2048*sizeof(float) = 256 Кбайт



Matrix Multiplication. Shared memory

- Divide each strip into square matrix (32*32)
- Then required submatrix C' can be represented as a sum of products of such matrices 32*32
- For calculations we need only two matrix 32*32 in shared-memory

$$C' = A'_1 * B'_1 + ... + A'_{N/32} * B'_{N/32}$$



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B

4*32*32*sizeof(float) = 16 Кбайт

Matrix Multiplication. Shared memory. Kernel

```
global void matMult 1 ( float * a, float * b, int n, float * c ) {
 int bx = blockIdx.x, by = blockIdx.y;
 int tx = threadIdx.x, ty = threadIdx.y;
 int aBegin = n * BLOCK SIZE * by;
 int aEnd = aBegin + n - 1;
 int bBegin = BLOCK SIZE * bx;
 int aStep = BLOCK SIZE, bStep = BLOCK SIZE * n;
 float sum = 0.0f;
  shared float as [BLOCK SIZE] [BLOCK SIZE];
 shared float bs [BLOCK SIZE] [BLOCK SIZE];
 for ( int ia = aBegin, ib = bBegin; ia <= aEnd;
                                   ia += aStep, ib += bStep){
    as [tx][ty] = a [ia + n * ty + tx];
    bs [tx][ty] = b [ib + n * ty + tx];
    syncthreads ();
    for ( int k = 0; k < BLOCK SIZE; k++)
       sum += as [k][ty] * bs [tx][k];
    syncthreads ();
 c [aBegin + bBegin + n * ty + tx] = sum;
```

Matrix Multiplication. Results

Sequential code:

CPU: Intel Core i7 58-20K 3,3 GHz

Dram: 16 GB

GPU code:

Name: GeForce GTX 960

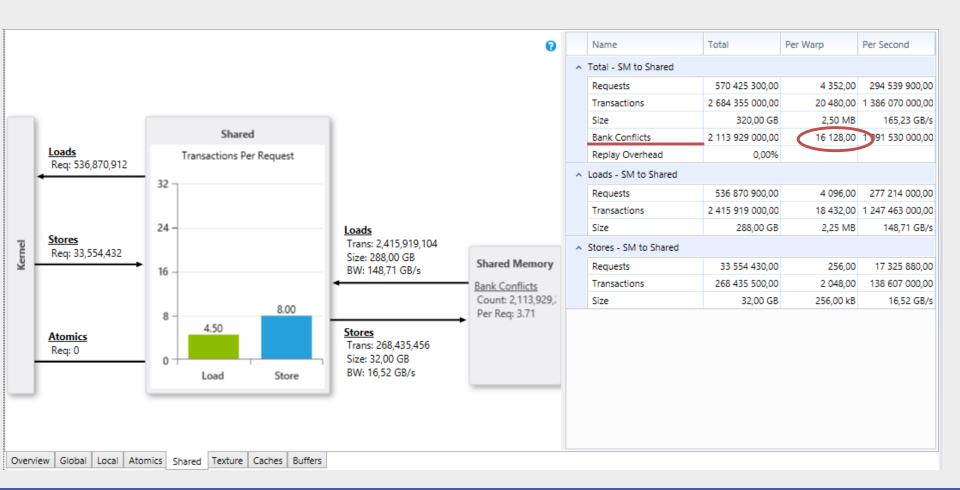
Compute capability: 5.2

	Execution Time	Rate
Sequential code	69773,2	-
Global Memory	3230	21,6
Shared Memory	3151,4	22,14



CUDA Toolkit. Profiling

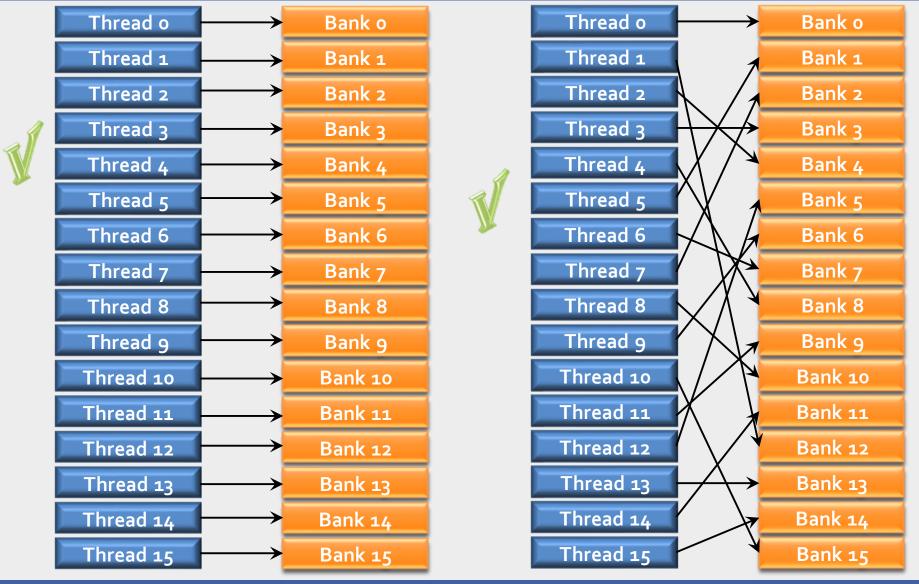
- Visual Profiler
- NSight



Shared Memory. Bank conflicts

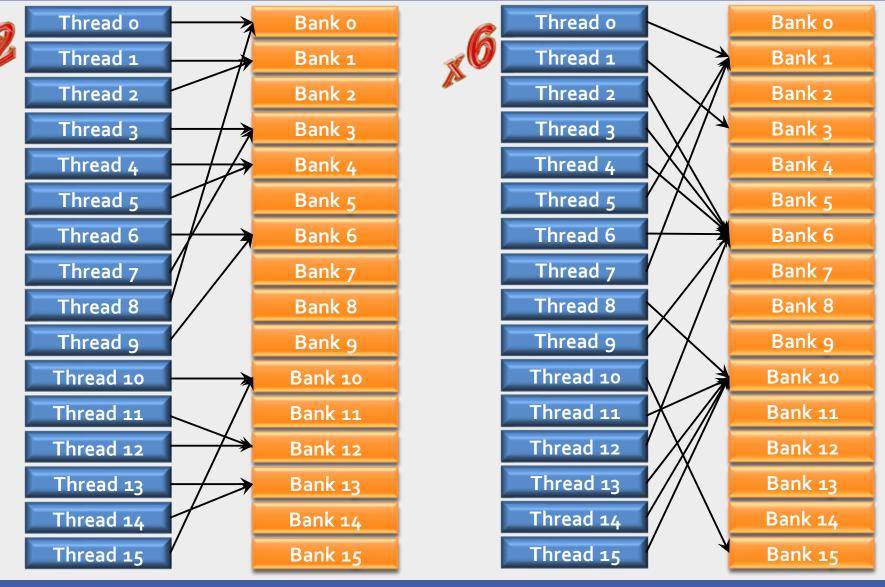
- shared memory is divided into equally sized memory modules (banks) that can be accessed simultaneously.
- Shared memory banks are organized such that successive 32-bit words are assigned to successive banks and the bandwidth is 32 bits per bank per clock cycle.
- If multiple threads' requested addresses map to the same memory bank, the accesses are serialized (Bank conflicts).

Shared Memory. Bank conflicts





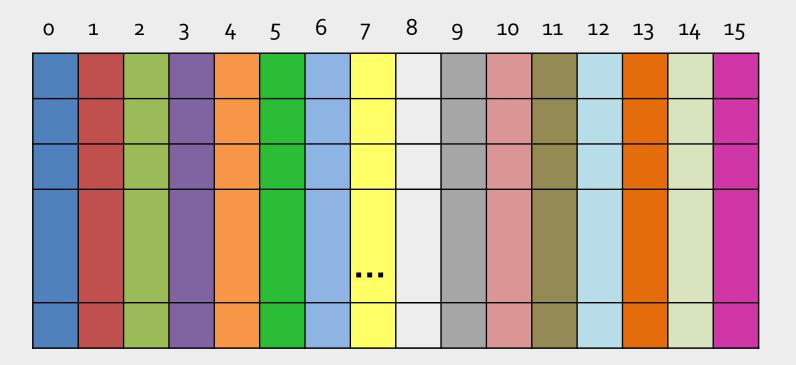
Shared Memory. Bank conflicts





Sample. Matrix Multiplication (16*16)

- The multiplication of two matrices 16*16, located in the shared memory
- Access to one matrix is by rows, to the another by columns

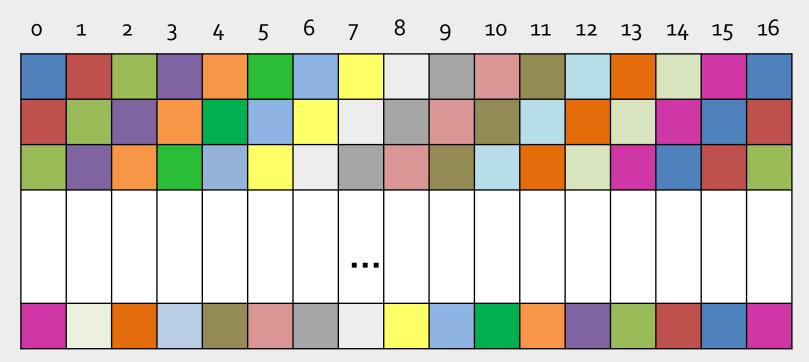


- All of the elements of the row are distributed evenly across the 16 banks. There are no conflicts
- All the elements of a column are in one Bank. 16-th order bank conflict



Sample. Matrix Multiplication (16*16)

• Complete each line with one (fictitious) element



- All column elements are in different banks
- Actually, by slightly increasing the amount of memory completely got rid of the conflicts



Matrix Multiplication. Shared memory. V.2

```
global void matMult 2 ( float * a, float * b, int n, float * c ) {
 int bx = blockIdx.x, by = blockIdx.y;
 int tx = threadIdx.x, ty = threadIdx.y;
 int aBegin = n * BLOCK SIZE * by;
 int aEnd = aBegin + n - 1;
 int bBegin = BLOCK SIZE * bx;
 int aStep = BLOCK SIZE, bStep = BLOCK SIZE * n;
 float sum = 0.0f;
  shared float as [BLOCK SIZE] [BLOCK SIZE+1];
 shared float bs [BLOCK SIZE] [BLOCK SIZE+1];
 for ( int ia = aBegin, ib = bBegin; ia <= aEnd;
                                   ia += aStep, ib += bStep){
    as [tx][ty] = a [ia + n * ty + tx];
    bs [tx][ty] = b [ib + n * ty + tx];
    syncthreads ();
    for ( int k = 0; k < BLOCK SIZE; k++)
       sum += as [k][ty] * bs [tx][k];
    syncthreads ();
 c [aBegin + bBegin + n * ty + tx] = sum;
```



Matrix Multiplication. Shared memory. v.3

```
global void matMult 2 ( float * a, float * b, int n, float * c ) {
 int bx = blockIdx.x, by = blockIdx.y;
 int tx = threadIdx.x, ty = threadIdx.y;
 int aBegin = n * BLOCK SIZE * by;
 int aEnd = aBegin + n - 1;
 int bBegin = BLOCK SIZE * bx;
 int aStep = BLOCK SIZE, bStep = BLOCK SIZE * n;
 float sum = 0.0f;
  shared float as [BLOCK SIZE] [BLOCK SIZE];
 shared float bs [BLOCK SIZE] [BLOCK SIZE];
 for ( int ia = aBegin, ib = bBegin; ia <= aEnd;
                                   ia += aStep, ib += bStep){
    as [ty][tx] = a [ia + n * ty + tx];
    bs [ty][tx] = b [ib + n * ty + tx];
    syncthreads ();
    for ( int k = 0; k < BLOCK SIZE; k++)
       sum += as [ty][k] * bs [k][tx];
    syncthreads ();
 c [aBegin + bBegin + n * ty + tx] = sum;
```

Matrix Multiplication. Results

Sequential code:

CPU: Intel Core i7 58-20K 3,3 GHz

• Dram: 16 GB

• GPU code:

Name :GeForce GTX 960

Compute capability: 5.2

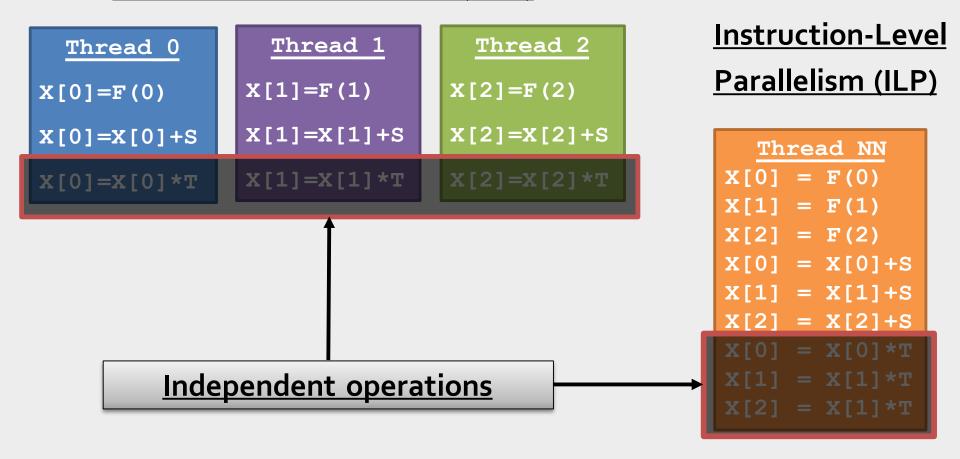
	Execution Time	Rate
Sequential code	69773,2	-
Global Memory	3230	21,6
Shared Memory 1	3151,4	22,14
Shared Memory 2/3	1652	42,5





TLP vs ILP

Thread-Level Parallelism (TLP)



Matrix Multiplication. Shared memory. v.4

Instead of lines in kernel (in v.3)

```
float sum = 0.0f;
as [ty][tx] = a [ia + n * ty + tx];
bs [ty][tx] = b [ib + n * ty + tx];
sum += as [ty][k] * bs [k][tx];
c [aBegin + bBegin + n * ty + tx] = sum;
```

Following lines

```
float sum1 = 0.0f, sum2 = 0.0f;
as[ty][tx] = a[ia + n * ty + tx];
bs[ty][tx] = b[ib + n * ty + tx];
as[ty+16][tx] = a[ia + n * (ty + 16) + tx];
bs[ty+16][tx] = b[ib + n * (ty + 16) + tx];
sum1 += as[ty][k] * bs[k][tx];
sum2 += as[ty + 16][k] * bs[k][tx];
c[aBegin + bBegin + n * ty + tx] = sum1;
c[aBegin + bBegin + n * (ty + 16) + tx] = sum2;
```

Add lines in 'main'

```
dim3 threads_4(BLOCK_SIZE, BLOCK_SIZE / 2);
matMult_Shared_mem4 << <blocks, threads_4 >> > (d_A, d_B, N, d_C);
```



Matrix Multiplication. Results

Sequential code:

CPU: Intel Core i7 58-20K 3,3 GHz

• Dram: 16 GB

• GPU code:

Name :GeForce GTX 960

Compute capability: 5.2

	Execution Time	Rate
Sequential code	69773,2	-
Global Memory	3230	21,6
Shared Memory 1	3151,4	22,14
Shared Memory 2/3	1652	42,5
Shared Memory 4	1421,5	49,1



Matrix Multiplication. Shared memory. v.5

Add following lines in kernel

```
float sum1 = 0.0f, sum2 = 0.0f, sum3 = 0.0f, sum4 = 0.0f;
as[ty][tx] = a[ia + n * ty + tx];
bs[ty][tx] = b[ib + n * ty + tx];
as[ty + 8][tx] = a[ia + n * (ty + 8) + tx];
bs[ty + 8][tx] = b[ib + n * (ty + 8) + tx];
as[ty + 16][tx] = a[ia + n * (ty + 16) + tx];
bs[ty + 16][tx] = b[ib + n * (ty + 16) + tx];
as[ty + 24][tx] = a[ia + n * (ty + 24) + tx];
bs[ty + 24][tx] = b[ib + n * (ty + 24) + tx];
sum1 += as[ty][k] * bs[k][tx];
sum2 += as[ty + 8][k] * bs[k][tx];
sum3 += as[ty + 16][k] * bs[k][tx];
sum4 += as[ty + 24][k] * bs[k][tx];
c[aBegin + bBegin + n * ty + tx] = sum1;
c[aBegin + bBegin + n * (ty + 8) + tx] = sum2;
c[aBegin + bBegin + n * (ty + 16) + tx] = sum3;
c[aBegin + bBegin + n * (ty + 24) + tx] = sum4;
```

Changes in 'main'

```
dim3 threads_5(BLOCK_SIZE, BLOCK_SIZE / 4);
matMult_Shared_mem4 << <blocks, threads_5 >> > (d_A, d_B, N, d_C);
```



Matrix Multiplication. Results

Sequential code:

CPU: Intel Core i7 58-20K 3,3 GHz

Dram: 16 GB

• GPU code:

Name :GeForce GTX 960

Compute capability: 5.2

	Execution Time	Rate
Sequential code	69773,2	-
Global Memory	3230	21,6
Shared Memory 1	3151,4	22,14
Shared Memory 2/3	1652	42,5
Shared Memory 4	1421,5	49,1
Shared Memory 5	1258,8	55,4





3 Ways to Accelerate Applications

Applications

Libraries

OpenACC Directives

Programming Languages

"Drop-in" Acceleration

Easily Accelerate Applications

Maximum Flexibility



GPU Programming Languages

Numerical analytics > MATLAB, Mathematica, LabVIEW Fortran > OpenACC, CUDA Fortran C OpenACC, CUDA C C++ | Thrust, CUDA C++ Python > PyCUDA, Copperhead F# | Alea.cuBase

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3 Ways to Accelerate Applications

Applications

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"Drop-in"
Acceleration

Easily Accelerate Applications

Maximum Flexibility



Libraries: Easy, High-Quality Acceleration

 Easy of use: Using libraries enables GPU acceleration without in-depth knowledge of GPU programming

 "Drop-in": Many GPU-accelerated libraries follow standard APIs, thus enabling acceleration with minimal code changes

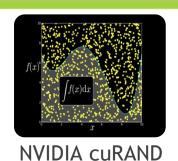
• Quality: Libraries offer high-quality implementations of functions encountered in a broad range of applications

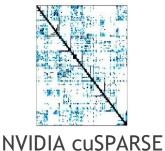
• Performance: NVIDIA libraries are tuned by experts



Some GPU-accelerated Libraries











Vector Signal Image Processing



GPU Accelerated Linear Algebra



on GPU and Multicore



NVIDIA cuFFT







Sparse Linear Algebra



C++ STL Features for CUDA

Matrix Multiplication. Results

Sequential code:

CPU: Intel Core i7 58-20K 3,3 GHz

• Dram: 16 GB

• GPU code:

Name :GeForce GTX 960

Compute capability: 5.2

	Execution Time	Rate
Sequential code	69773,2	-
Global Memory	3230	21,6
Shared Memory 1	3151,4	22,14
Shared Memory 2/3	1652	42,5
Shared Memory 4	1421,5	49,1
Shared Memory 5	1258,8	55,4
CUBLAS	188	371





Just one "but"...

Sequential code:

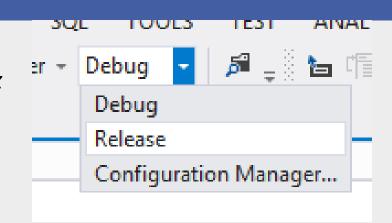
• CPU: Intel Core i7 58-20K 3,3 GHz

• *Dram:* 16 *GB*

GPU code:

Name: GeForce GTX 960

Compute capability: 5.2



	Execution Time (Debug)	Rate (Debug)	Execution Time (Release)	Rate (Release)
Sequential code	69773,2	-	35665,4	-
Global Memory	3230	21,6	188,2	189,5
Shared Memory 1	3151,4	22,14	179	199,2
Shared Memory 2/3	1652	42,5	80,7	442
Shared Memory 4	1421,5	49,1	45,7	780,4
Shared Memory 5	1258,8	55,4	37,3	956,2
CUBLAS	188	371	187,4	190,3

3 Ways to Accelerate Applications

Applications

Libraries

OpenACC Directives

Programming Languages

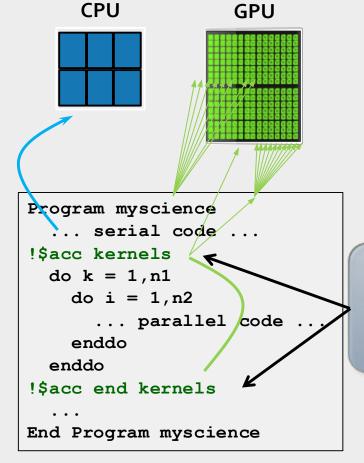
"Drop-in" Acceleration

Easily Accelerate Applications

Maximum Flexibility



OpenACC Directives



OpenACC compiler Hint

Simple Compiler hints

Compiler Parallelizes code

Works on many-core GPUs & multicore CPUs

Your original Fortran or C code

OpenACC Directives

• **Easy:** Directives are the easy path to accelerate compute intensive applications

 Open: OpenACC is an open GPU directives standard, making GPU programming straightforward and portable across parallel and multi-core processors

 Powerful: GPU Directives allow complete access to the massive parallel power of a GPU

Further read

- CUDA Programming Guide, http://docs.nvidia.com/cuda/cuda-c-programming-guide/
- CUDA C Best Practices Guide, <u>http://docs.nvidia.com/cuda/cuda-c-best-practices-guide</u>

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