

Faculty of Mathematics and Information Science

WARSAW UNIVERSITY OF TECHNOLOGY

Graphic Processors in Computational Applications

Part 2 – CUDA Advances

dr inż. Krzysztof Kaczmarski 2021



Rzeczpospolita Polska Politechnika Warszawska

Unia Europejska Europejski Fundusz Społeczny



Materiały sponsorowane przez:

Projekt "NERW 2 PW. Nauka – Edukacja – Rozwój – Współpraca" współfinansowany jest ze środków Unii Europejskiej w ramach Europejskiego Funduszu Społecznego

Zadanie 10 pn. "Modyfikacja programów studiów na kierunkach prowadzonych przez Wydział Matematyki i Nauk Informacyjnych", realizowane w ramach projektu "NERW 2 PW. Nauka – Edukacja – Rozwój – Współpraca", współfinansowanego jest ze środków Unii Europejskiej w ramach Europejskiego Funduszu Społecznego



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Goals for today:

- Understand advanced CUDA techniques
- Get familiar with pitfalls of parallel programming



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Part 2 – CUDA Advances

Warp threads scheduling

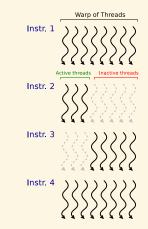
Advanced synchronization

Variables and Memory Memory types Global Memory Access Shared Memory Example of shared memory utilization – matrices

- Asynchronous operations
- Problems of parallelism Race conditions Volatile
- Time Measurements

- 1 instruction 1
- 2 if (threadIdx.x<4)</pre>
- 3 instruction 2
- 4 else
- 5 instruction 3
- 6 instruction 4

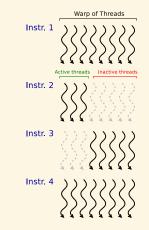
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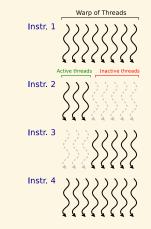
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A single thread is assigned to a single ALU. Waste of bandwidth – some ALUs do nothing.

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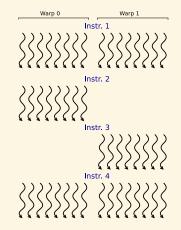
Common mistake: Instr 2. before Instr. 3

Warp of Threads Instr. 1 Active threads Inactive t Instr. 2 Instr. 3 Instr. 4

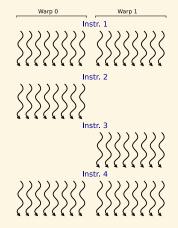
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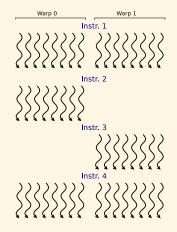


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Warp-level control saves bandwidth in conditional operations.



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- void __syncwarp(unsigned mask=0xffffffff); will cause the executing thread to wait until all warp lanes named in mask have executed a __syncwarp() (with the same mask) before resuming execution. All non-exited threads named in mask must execute a corresponding __syncwarp() with the same mask, or the result is undefined.

Advanced synchronization

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 - All threads in the device for global memory accesses.



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Variables and Memory

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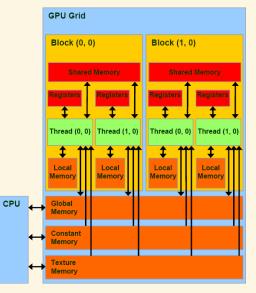
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Accessing different types of memory

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Global Memory Operations

Variables and Memory

Memory operations are executed per warp

- 32 threads in a warp provide memory addresses
- Hardware determines into which lines those addresses fall
- Stores:

Invalidate L1, go at least to L2, 32-byte granularity

- Three types of loads:
 - Caching (default)
 - Non-caching
 - Read-only

Memory Load

Variables and Memory

Caching (default mode)

- Attempts to hit in L1, then L2, then GMEM
- Load granularity is 128-byte line
- Non-caching
 - Compile with -Xptxas -dlcm=cg option to nvcc
 - Attempts to hit in L2, then GMEM (Does not hit in L1, invalidates the line if it's in L1 already)
 - Load granularity is 32 bytes

Read-only

- Loads via read-only cache: (Attempts to hit in Read-only cache, then L2, then GMEM)
- Load granularity is 32 bytes

Coalesced Global Memory Access

Perhaps the most important optimization

Global memory loads and stores by threads of a warp are coalesced by the device into as few as possible transactions.

Compute capability ≥ 6.0 (since pascal)

The concurrent accesses of the threads of a warp will coalesce into a number of transactions equal to the number of 32-byte transactions necessary to service all of the threads of the warp.

Compute capability < 5.2 (before pascal)

L1-caching of accesses to global memory can be optionally enabled. If L1-caching is enabled on these devices, the number of required transactions is equal to the number of required 128-byte aligned segments.

Simple Access Pattern (cc \geq 6.0)

Variables and Memory



- The k-th thread accesses the k-th word in a 32-byte aligned array.
- If the threads of a warp access adjacent 4-byte words
- ...and not all equally participate
- ...and/or random permuted access inside the block
- then still only four 32-byte transactions would have been performed by a device.

NVIDIA CUDA Toolkit. Cuda c++ best practices guide.

https://docs.nvidia.com/cuda/cuda-c-best-practices-guide/index.html, 2020

Misaligned Sequential Access Pattern (cc>6.0)



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1 __global__ void offsetCopy(float *odata,
2 float *idata,
3 int offset)
4 {
5 int xid = blockIdx.x * blockDim.x +
6 threadIdx.x + offset;
7 odata[xid] = idata[xid];
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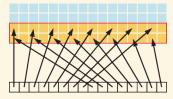
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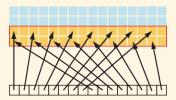
Strided Access Pattern



- A stride of 2 results in a 50% of load/store efficiency since half the elements in the transaction are not used and represent wasted bandwidth.
- As the stride increases, the effective bandwidth decreases until the point where 32 32-byte segments are loaded for the 32 threads in a warp.

Strided Access Pattern

Variables and Memory



1

2

3

4

5

6

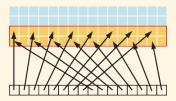
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8

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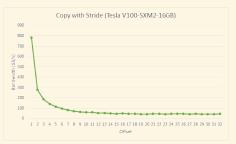
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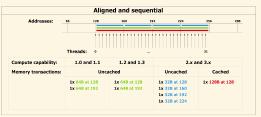


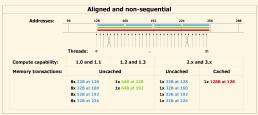
 Avoid non-unit-stride global memory accesses – use shared memory.

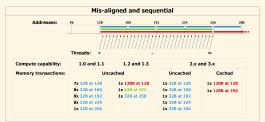
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In older architectures

(not supported now)







 $21 \, / \, 60$

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 - width is a multiply of 16
 - The width of the thread block is a multiple of half the warp size

Variables and Memory

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AoS	x_1	y_1	z_1	w_1	x_2	y_2	z_2	w_2
	x_3	y_3	z_3	w_3	x_4	y_4	z_4	

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	x_3	y_3	z_3	w_3	x_4	y_4	z_4	

SoA	x_1	x_2	x_3	x_4	 	
	y_1	y_2	y_3	y_4	 	
	z_1	z_2	z_3	z_4	 	
	w_1	w_2	w_3	w_4	 	

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	y_1	y_2	y_3	y_4	 	
	z_1	z_2	z_3	z_4	 	
	w_1	w_2	w_3	w_4	 	

Use __align(4), __align(8) or __align(16) in structure declarations

Coalescing example I

Variables and Memory

```
Misaligned memory access with float3 data
```

```
global void accessFloat3(float3 *d_in, float3 *d_out)
1
  Ł
2
     int index = blockIdx.x * blockDim.x + threadIdx.x;
3
     float3 a = d_in[index];
4
     a.x += 2;
   a.v += 2;
6
     a.z += 2:
7
     d out[index] = a;
8
  }
g
```

 Each thread reads 3 floats = 12 bytes
 Half warp reads 16 * 12 = 192 bytes (three 64B non-contiguous segments)

NVIDIA. Cuda whitepapers. www.nvidia.com/cuda

Coalescing example II

Variables and Memory

Coalesced memory access with float3 data

```
__global__ void accessFloat3Shared(float *g_in, float *g_out)
 1
   Ł
 2
      int index = 3 * blockIdx.x * blockDim.x + threadIdx.x;
3
      __shared__ float s_data[256*3];
 4
      s_data[threadIdx.x] = g_in[index];
 5
      s_data[threadIdx.x+256] = g_in[index+256];
6
      s_data[threadIdx.x+512] = g_in[index+512];
7
      _____syncthreads();
8
      float3 a = ((float3*)s data)[threadIdx.x];
9
10
      a.x += 2:
11
      a.v += 2;
      a.z += 2:
12
      ((float3*)s_data)[threadIdx.x] = a;
13
      __syncthreads();
14
      g_out[index] = s_data[threadIdx.x];
15
      g_out[index+256] = s_data[threadIdx.x+256];
16
      g_out[index+512] = s_data[threadIdx.x+512];
17
   }
18
```



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Example of shared memory utilization - matrices

Asynchronous operations

Problems of parallelism Race conditions Volatile

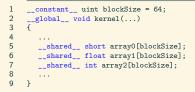
Time Measurements

Allocating shared memory

Variables and Memory

Static way

Device side:



Host side:

1 kernel <<< nBlocks, blockSize >>>(...);

Allocating shared memory

Variables and Memory

Static way Device side:

```
constant uint blockSize = 64;
2
    __global__ void kernel(...)
3
5
      shared short array0[blockSize];
6
      __shared__ float array1[blockSize];
7
      shared int array2[blockSize];
8
9
   }
```

Host side:

kernel<<< nBlocks, blockSize >>>(...); 1

Dynamic way Device side:

2

3 4

6

7

8

9

10

1

4

```
constant uint blockSize = 64;
__global__ void kernel(...)
  extern shared float array[];
  //All variables declared in this fashion,
        start at the same address in memory, so:
  short* array0 = (short*)array;
  float* arrav1 = (float*)&arrav0[blockSize];
  int* array2 = (int*)&array1[blockSize];
```

Host side:

```
smBytes = blockSize*sizeof(float)
2
           + blockSize*sizeof(short)
3
           + blockSize*sizeof(int):
5
```

kernel<<< nBlocks, blockSize, smBytes >>>(...);

Allocating shared memory

Variables and Memory

Static way

```
constant uint blockSize = 64;
                                                      constant uint blockSize = 64;
2
    __global__ void kernel(...)
                                                  2
                                                      __global__ void kernel(...)
3
                                                  3
                                                  4
                                                         extern shared float array[];
5
      shared short array0[blockSize];
                                                         //All variables declared in this fashion,
6
      __shared__ float array1[blockSize];
                                                               start at the same address in memory, so:
7
      shared int array2[blockSize];
                                                  6
8
                                                  7
                                                         short* array0 = (short*)array;
9
                                                  8
                                                         float* arrav1 = (float*)&arrav0[blockSize];
                                                  9
                                                         int* array2 = (int*)&array1[blockSize];
                                                 10
      Host side:
                                                         Host side:
    kernel<<< nBlocks, blockSize >>>(...);
1
                                                      smBytes = blockSize*sizeof(float)
                                                  2
                                                             + blockSize*sizeof(short)
                                                  3
                                                             + blockSize*sizeof(int):
                                                  4
                                                  5
                                                      kernel<<< nBlocks, blockSize, smBytes >>>(...);
```

Note that pointers need to be aligned to the type they point to. Error: array1 is not aligned to 4 bytes:

```
1 short* array0 = (short*)array;
```

```
2 float* array1 = (float*)&array0[127];
```

Dynamic way Device side:

Variables and Memory

Shared memory is divided into equally sized memory modules, called **banks**.

Variables and Memory

Shared memory is divided into equally sized memory modules, called banks.

Different banks can be accessed simultaneously.

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- Different banks can be accessed simultaneously.
- Read or write to n addresses in n banks multiplies bandwidth of a single bank by n.

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- Different banks can be accessed simultaneously.
- Read or write to n addresses in n banks multiplies bandwidth of a single bank by n.
- If many threads refers the same bank the access is serialized hardware splits a memory request that has bank conflicts into as many separate conflict-free requests as necessary.

- Shared memory is divided into equally sized memory modules, called banks.
- Different banks can be accessed simultaneously.
- Read or write to n addresses in n banks multiplies bandwidth of a single bank by n.
- If many threads refers the same bank the access is serialized hardware splits a memory request that has bank conflicts into as many separate conflict-free requests as necessary.
- There is one exception if all threads within a half-warp accesses the same address.

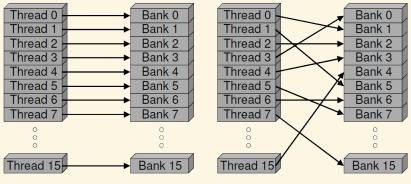
Bank conflicts

Variables and Memory

Shared memory banks are organized in such a way that successive 32-bit words are assigned to successive banks and each bank has a bandwidth of 32 bits per clock cycle. The bandwidth of shared memory is 32 bits per bank per clock cycle.

Access with no bank conflicts

Variables and Memory

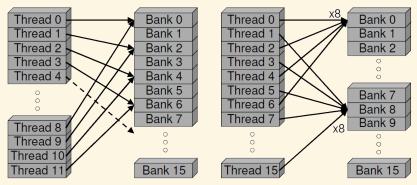


left: stride = 1 right: stride random

NVIDIA. Cuda whitepapers. www.nvidia.com/cuda

Access with bank conflicts

Variables and Memory



left: stride = 2 (2 way bank conflict) right: stride = 8 (8 way bank conflict)

NVIDIA. Cuda whitepapers. www.nvidia.com/cuda

Padding – adding extra space between array elements in order to brake cyclic access to same bank.

Example of bank conflicts removal in reduction I

Variables and Memory

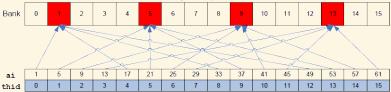
Addressing Without Padding

int ai = offset*(2*thid+1)-1; int bi = offset*(2*thid+2)-1; temp[bi] += temp[ai];

offset = 1: Address (ai) stride is 2, resulting in 2-way bank conflicts







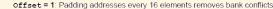
Mark Harris. Parallel prefix sum (scan) with CUDA. www.nvidia.com/cuda, 2007

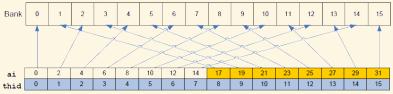
Example of bank conflicts removal in reduction II

Variables and Memory

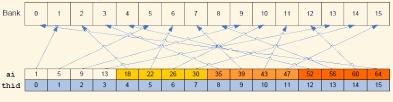
Addressing With Padding

```
int ai = offset*(2*thid+1)-1;
int bi = offset*(2*thid+2)-1;
ai += ai / NUM_BANKS;
bi += bi / NUM_BANKS;
temp[bi] += temp[ai];
```

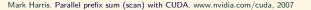




Offset = 2: Padding addresses every 16 elements removes bank conflicts



Padding increment:



Variables and Memory

We need more space in shared memory:

unsigned int extra_space = num_elements / NUM_BANKS;

Variables and Memory

We need more space in shared memory:

```
unsigned int extra_space = num_elements / NUM_BANKS;
```

Padding macro:

- 1 #define NUM_BANKS 16
- 2 #define LOG_NUM_BANKS 4
- 3
- 4 **#ifdef** ZERO_BANK_CONFLICTS
- 5 #define CONFLICT_FREE_OFFSET(index) ((index) >> LOG_NUM_BANKS \

+ (index) >> (2 * LOG NUM BANKS))

- 6
- 7 **#else**
- 8 #define CONFLICT_FREE_OFFSET(index) ((index) >> LOG_NUM_BANKS)
- 9 **#endif**

Variables and Memory

We need more space in shared memory:

```
unsigned int extra_space = num_elements / NUM_BANKS;
1
    Padding macro:
  #define NUM BANKS 16
1
  #define LOG_NUM_BANKS 4
2
3
  #ifdef ZERO_BANK_CONFLICTS
4
  #define CONFLICT_FREE_OFFSET(index) ((index) >> LOG_NUM_BANKS \
5
                                   + (index) >> (2 * LOG_NUM_BANKS))
6
  #else
7
  #define CONFLICT FREE OFFSET(index) ((index) >> LOG NUM BANKS)
8
  #endif
a
```

Zero bank conflicts requires even more additional space:

1 **#ifdef** ZERO_BANK_CONFLICTS

```
2 extra_space += extra_space / NUM_BANKS;
```

```
3 #endif
```

Mark Harris. Parallel prefix sum (scan) with CUDA. www.nvidia.com/cuda, 2007

Variables and Memory

Loading data into shared memory:

```
int ai = thid, bi = thid + (n/2);
// compute spacing to avoid bank conflicts
int bankOffsetA = CONFLICT_FREE_OFFSET(ai);
int bankOffsetB = CONFLICT_FREE_OFFSET(bi);
TEMP(ai + bankOffsetA) = g_idata[ai];
TEMP(bi + bankOffsetB) = g_idata[bi];
```

Variables and Memory

Loading data into shared memory:

```
int ai = thid, bi = thid + (n/2);
1
2
   // compute spacing to avoid bank conflicts
3
   int bankOffsetA = CONFLICT FREE OFFSET(ai);
   int bankOffsetB = CONFLICT_FREE_OFFSET(bi);
5
6
  TEMP(ai + bankOffsetA) = g_idata[ai];
7
  TEMP(bi + bankOffsetB) = g_idata[bi];
8
    Algorithm:
  int ai = offset*(2*thid+1)-1:
1
   int bi = offset*(2*thid+2)-1;
2
3
   ai += CONFLICT_FREE_OFFSET(ai);
4
   bi += CONFLICT FREE OFFSET(bi);
6
  TEMP(bi) += TEMP(ai);
7
```

Mark Harris. Parallel prefix sum (scan) with CUDA. www.nvidia.com/cuda, 2007



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Part 2 – CUDA Advances

Warp threads scheduling

Advanced synchronization

Variables and Memory

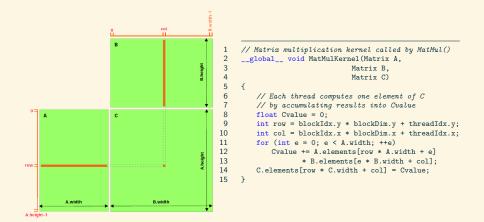
Memory types Global Memory Access Shared Memory Example of shared memory utilization – matrices

Asynchronous operations

Problems of parallelism Race conditions Volatile

Time Measurements

No shared memory used



Host program for clarity

void MatMul(const Matrix A,	22
const Matrix B,	23
Matrix C)	24
{	25
<pre>// Load A and B to device memory</pre>	26
Matrix d_A;	27
d_A.width = A.width; d_A.height = A.heig	ght; 28
size_t size = A.width * A.height	29
<pre>* sizeof(float);</pre>	30
	31
<pre>cudaMalloc(&d_A.elements, size);</pre>	32
cudaMemcpy(d_A.elements, A.elements, siz	ze, 33
cudaMemcpyHostToDevice);	34
Matrix d_B;	35
d_B.width = B.width;	36
d_B.height = B.height;	37
size = B.width * B.height * sizeof(float	; 38
	39
<pre>cudaMalloc(&d_B.elements, size);</pre>	40
cudaMemcpy(d_B.elements, B.elements, siz	ze, 41
cudaMemcpyHostToDevice);	42
	43

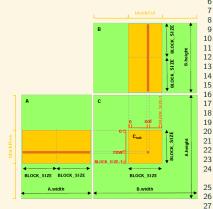
```
// Allocate C in device memory
Matrix d C:
d_C.width = C.width; d_C.height = C.height;
size = C.width * C.height * sizeof(float);
cudaMalloc(&d C.elements, size):
```

```
// Invoke kernel
dim3 dimBlock(BLOCK SIZE, BLOCK SIZE);
dim3 dimGrid(B.width / dimBlock.x,
            A.height / dimBlock.y);
MatMulKernel <<< dimGrid. dimBlock>>>
             (d A, d B, d C):
```

```
// Read C from device memory
cudaMemcpy(C.elements, d_C.elements, size,
          cudaMemcpyDeviceToHost);
```

```
// Free device memory
cudaFree(d_A.elements);
cudaFree(d B.elements);
cudaFree(d C.elements);
```

with shared memory used I



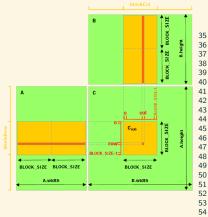
NVIDIA. Cuda c++ programming guide.

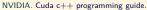
www.nvidia.com/cuda

```
typedef struct {
        int width;
 3
        int height;
 Δ
        int stride;
 5
        float* elements;
 6
     } Matrix:
     device float GetElement(const Matrix A,
                              int row. int col)
     ſ
        return A.elements[row * A.stride + col];
     }
     device void SetElement(Matrix A, int row,
                             int col, float value)
     ſ
        A.elements[row * A.stride + col] = value:
     3
     // Get the BLOCK_SIZExBLOCK_SIZE sub-matrix Asub
     // of A located col sub-matrices to the right and
     // row sub-matrices down from the upper-left corner
     // of A
      device Matrix GetSubMatrix(Matrix A, int row,
            int col)
     ſ
        Matrix Asub:
        Asub.width = BLOCK_SIZE;
28
        Asub.height = BLOCK SIZE:
29
        Asub.stride = A.stride:
30
        Asub.elements = &A.elements[A.stride
31
                                  * BLOCK SIZE * row
32
                                  + BLOCK SIZE * coll:
33
        return Asub;
34
```

3

with shared memory used II





www.nvidia.com/cuda

```
__global__ void MatMulKernel(Matrix A,
Matrix B,
Matrix C)
{
    // Block row and columm
    int blockRow = blockIdx.y;
    int blockCol = blockIdx.x;
    // Each thread block computes one sub-matrix
    // Csub of C
Matrix Csub = GetSubMatrix(C, blockRow.
```

// Each thread computes one element of Csub
// by accumulating results into Cvalue
float Cvalue = 0;

```
// Thread row and column within Csub
int row = threadIdx.y;
int col = threadIdx.x;
```

51

52

53

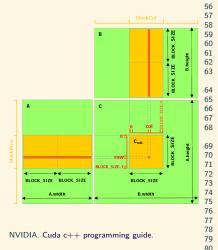
54

55

81

82 }

with shared memory used III



www.nvidia.com/cuda

```
for (int m = 0; m < (A.width / BLOCK_SIZE); ++m)</pre>
   // Get sub-matrix Asub of A
   Matrix Asub = GetSubMatrix(A, blockRow, m);
   // Get sub-matrix Bsub of B
   Matrix Bsub = GetSubMatrix(B, m, blockCol);
   // Shared memory used to store Asub and Bsub
   __shared__ float As[BLOCK_SIZE][BLOCK_SIZE];
   shared float Bs[BLOCK SIZE][BLOCK SIZE];
   // Each thread loads one element of each sub
          -matrix
   As[row][col] = GetElement(Asub, row, col);
   Bs[row][col] = GetElement(Bsub, row, col);
   // Synchronize to make sure the sub-matrices
   // are loaded before starting the
          computation
   _____syncthreads();
   // Multiply Asub and Bsub together
   for (int e = 0; e < BLOCK_SIZE; ++e)</pre>
       Cvalue += As[row][e] * Bs[e][col]:
   // Synchronize to asure that the preceding
   // computation is done before loading new
   // sub-matrices of A and B
   syncthreads();
3
// Write Csub to device memory, one thread, one
      element
SetElement(Csub, row, col, Cvalue);
```



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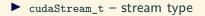
Asynchronous operations

• Applications manage concurrency through streams.

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cudaStream_t - stream type

cudaStreamCreate(&stream)

- Applications manage concurrency through streams.
- ► A stream is a sequence of commands that execute in order.
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- cudaStream_t stream type
- cudaStreamCreate(&stream)
- cudaStreamDestroy(&stream) waits for all tasks to complete before destroying a stream;

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- cudaStreamQuery() checks if all preceding commands in a stream have completed
- cudaStreamSynchronize() forces the run-time to wait until all preceding commands in a stream have completed.

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- cudaStreamDestroy(&stream) waits for all tasks to complete before destroying a stream;
- cudaStreamQuery() checks if all preceding commands in a stream have completed
- cudaStreamSynchronize() forces the run-time to wait until all preceding commands in a stream have completed.
- cudaThreadSynchronize() forces the run-time to wait until all preceding device tasks in all streams have completed

Streams API – example

Asynchronous operations

NVIDIA. Cuda c++ programming guide. www.nvidia.com/cuda

```
cudaStream t stream[2];
1
   for (int i = 0; i < 2; ++i)</pre>
2
      cudaStreamCreate(&stream[i]);
 3
   float* hostPtr:
4
   cudaMallocHost((void**)&hostPtr, 2 * size, cudaHostAllocDefault);
5
   cudaMalloc((void**)&inputDevPtr, 2 * size);
6
   cudaMalloc((void**)&outputDevPtr, 2 * size);
7
   for (int i = 0; i < 2; ++i)
8
      cudaMemcpyAsync(inputDevPtr + i * size, hostPtr + i * size,
9
                size, cudaMemcpyHostToDevice, stream[i]);
10
   for (int i = 0; i < 2; ++i)
11
      myKernel <<<100, 512, 0, stream[i]>>>
12
                (outputDevPtr + i * size, inputDevPtr + i * size, size);
13
   for (int i = 0; i < 2; ++i)
14
      cudaMemcpyAsync(hostPtr + i * size, outputDevPtr + i * size,
15
                size, cudaMemcpyDeviceToHost, stream[i]);
16
   cudaThreadSynchronize();
17
   for (int i = 0; i < 2; ++i)</pre>
18
      cudaStreamDestroy(&stream[i]);
19
```



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Problems of parallelism

Simplest possible operation (*x is a global memory pointer)

Let int *x point to global memory. *x++ happens in 3 steps:

- 1. Read the value in *x into a register.
- 2. Add 1 to the value in the register.
- 3. Write the result back to *x.

Problems of parallelism

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- 1 A: *x++
- 2 B: *x++

Problems of parallelism

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Let int *x point to global memory. *x++ happens in 3 steps:

- 1. Read the value in *x into a register.
- 2. Add 1 to the value in the register.
- 3. Write the result back to *x.

```
1 A: *x++

2 B: *x++

1 A: a = *x //a=7

2 B: b = *x //b=7

3 A: a++ //8

4 A: *x = a //8

5 B: b++ //8

6 B: *x = b //8
```

Problems of parallelism

```
#include <stdio.h>
 1
 2
     #include <stdlib.h>
     #include <cuda.h>
 4
     #include <cuda runtime.h>
 5
 6
     global void colonel(int *d a){
 7
       *d_a += 1;
8
     }
9
10
     int main(){
11
       int a = 0, *d a:
12
       cudaMalloc((void**) &a_d, sizeof(int));
13
       cudaMemcpy(d a, &a, sizeof(int), cudaMemcpyHostToDevice);
      float elapsedTime:
14
15
      cudaEvent t start, stop:
16
       cudaEventCreate(&start);
17
       cudaEventCreate(&stop);
18
       cudaEventRecord( start, 0 );
19
20
       colonel<<<1000,1000>>>(d_a);
21
22
       cudaEventRecord( stop, 0 );
23
       cudaEventSynchronize( stop );
       cudaEventElapsedTime( &elapsedTime, start, stop );
24
25
       cudaEventDestrov( start ):
26
       cudaEventDestroy( stop );
27
       printf("GPU_Time_::/%f_ms\n", elapsedTime);
28
29
       cudaMemcpy(&a, d_a, sizeof(int), cudaMemcpyDeviceToHost);
30
       printf("a_{l}=_{l}%d n", a):
31
32
       cudaFree(d a):
33
     3
```

Race condition results

Problems of parallelism

Output:

- 1 > nvcc race_condition.cu -o race_condition
- 2 > ./race_condition
- 3 GPU Time : 0.148 ms
- 4 a = 88

Race condition results

Problems of parallelism

Output:

- 1 > nvcc race_condition.cu -o race_condition
- 2 > ./race_condition
- 3 GPU Time : 0.148 ms
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Modification:

```
1 __global__ void colonel(int *d_a){
2 atomicAdd(d_a, 1);
3 }
```

Race condition results

Problems of parallelism

Output:

- 1 > nvcc race_condition.cu -o race_condition
- 2 > ./race_condition
- 3 GPU Time : 0.148 ms
- 4 a = 88

Modification:

```
1 __global__ void colonel(int *d_a){
2 atomicAdd(d_a, 1);
3 }
```

Output:

1 GPU Time : 14.85 ms

2 a = 1000000

Atomic functions can only be used in device functions.

Atomic operations I

(for all devices CC>2.0)

Device-wide atomics: atomic for all CUDA threads in the current program executing in the same compute device as the current thread:

- 1 atomicAdd()
- 2 atomicSub()
- 3 atomicMin()
- 4 atomicMax()
- 5 atomicInc()
- 6 atomicDec()
- 7 atomicAdd()
- 8 atomicExch()
- 9 atomicAnd()
- 10 atomicOr()
- 11 atomicXor()

12 int atomicCAS(int* address, int compare, int val); // Compare And Swap (returns old value)

An atomic function performs a read-modify-write atomic operation on one 32-bit or 64-bit word residing in global or shared memory.

Atomic operations II (for all devices CC≥6.0)

System-wide atomics: atomic for all threads in the current program including other CPUs and GPUs in the system. These are suffixed with _system. Like: atomicAdd_system().

Block-wide atomics: atomic for all CUDA threads in the current program executing in the same thread block as the current thread. These are suffixed with _block. Like: atomicAdd_block().



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 One of the compiler's tricks: reuse references to memory location

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- One of the compiler's tricks: reuse references to memory location
- Result: A reused value may be changed by another thread in the background

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- Result: A reused value may be changed by another thread in the background

```
// myArray is an array of non-zero integers
1
   // located in global or shared memory
2
   __global__ void myKernel(int* result)
3
   Ł
4
      int tid = threadIdx.x;
5
      int ref1 = myArray[tid] * 1;
6
      myArray[tid + 1] = 2;
7
      int ref2 = myArray[tid] * 1;
8
      result[tid] = ref1 * ref2;
9
10
  }
```

the first reference to myArray[tid] compiles into a memory read instruction

Problems of parallelism

- One of the compiler's tricks: reuse references to memory location
- Result: A reused value may be changed by another thread in the background

```
// myArray is an array of non-zero integers
1
   // located in global or shared memory
2
   __global__ void myKernel(int* result)
3
   Ł
4
      int tid = threadIdx.x;
5
      int ref1 = myArray[tid] * 1;
6
      myArray[tid + 1] = 2;
7
      int ref2 = myArray[tid] * 1;
8
      result[tid] = ref1 * ref2;
9
10
  }
```

- the first reference to myArray[tid] compiles into a memory read instruction
- the second reference does not as the compiler simply reuses the result of the first read



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Part 2 – CUDA Advances

Warp threads scheduling

Advanced synchronization

Variables and Memory Memory types Global Memory Access Shared Memory Example of shared memory utilization – matrices

Asynchronous operations

Problems of parallelism Race conditions Volatile

Timers API

- cudaEvent_t event type
- cudaEventSynchronize() blocks CPU until given event records
- cudaEventRecord() records given event in given stream
- cudaEventElapsedTime() calculates time in milliseconds between events
- cudaEventCreate() creates an event
- cudaEventDestroy() destroys an event

Timers Example

```
cudaEvent_t start, stop; float time;
1
   cudaEventCreate(&start):
 2
   cudaEventCreate(&stop);
3
 4
   cudaEventRecord( start, 0 );
6
   kernel<<<grid,threads>>> ( d_odata, d_idata, size_x, size_y);
 7
8
   cudaEventRecord( stop, 0 );
9
10
   cudaEventSynchronize( stop );
11
12
   cudaEventElapsedTime( &time, start, stop );
13
14
   cudaEventDestroy( start );
15
   cudaEventDestroy( stop );
16
```

Theoretical Bandwidth Calculation

$$\mathsf{TB} = (\mathsf{Clock} \times 10^6 \times \mathsf{MemInt} \times 2)/10^9$$

- ► TB theoretical bandwidth [GB/s]
- Clock memory clock rate [MHz]
- MemInt width of memory interface [B]
- 2 DDR Double Data Rate Memory

Theoretical Bandwidth Calculation

Time Measurements

$$\mathsf{TB} = (\mathsf{Clock} \times 10^6 \times \mathsf{MemInt} \times 2)/10^9$$

- ► TB theoretical bandwidth [GB/s]
- Clock memory clock rate [MHz]
- MemInt width of memory interface [B]
- 2 DDR Double Data Rate Memory

For NVIDIA GeForce GTX 280 we get:

 $(1107 \times 10^6 \times 512/8 \times 2)/10^9 = 141.6 \ [GB/s]$

Effective Bandwidth Calculation

$$EB = \frac{(B_r + B_w) \times 10^{-9}}{t}$$

- ► EB effective bandwidth [GB/s]
- ► B_r bytes read
- B_w bytes written
- ► *t* time of the test [s]

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