# Parallel Computing with GPUs: Parallel Patterns

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☐Parallel Patterns Overview

Reduction

**□**Scan



## What are parallel Patterns

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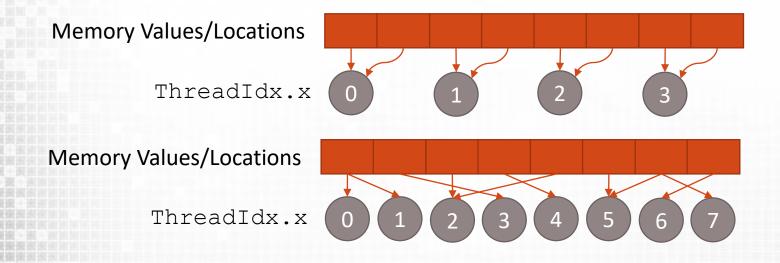
☐Parallel patterns are high level building blocks that can be used to create algorithms	)
□Implementation is abstracted to give a higher level view	
□ Patterns describe techniques suited to parallelism □ Allows algorithms to be built with parallelism from ground up □ Top down approach might not parallelise very easily	
□ Consider a the simplest parallel pattern: <i>Map</i> □ Takes the input list <i>i</i> □ Applies a function <i>f</i> □ Writes the result list <i>o</i> by applying <i>f</i> to all members of <i>i</i> □ Equivalent to a CUDA kernel where <i>i</i> and <i>o</i> are memory locations determ by threadIdx etc.	nined





#### Gather

- ☐ Multiple inputs and single coalesced output
- Might have sequential loading or random access
  - ☐ Affect memory performance
- ☐ Differs to map due to multiple inputs



Gather operation

☐ Read from a number of locations

Gather operation

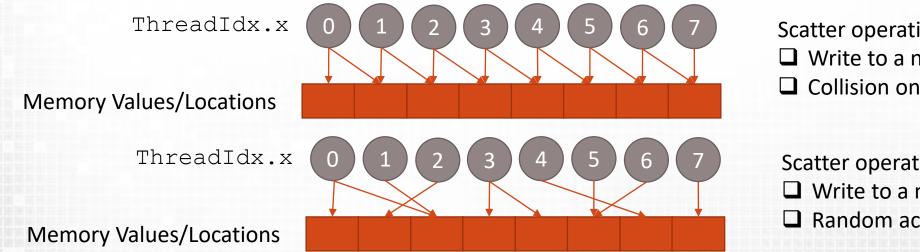
- ☐ Read from a number of locations
- ☐ Random access load





#### Scatter

- Reads from a single input and writes to one or many
- ☐ Can be implemented in CUDA using atomics
- ☐ Write pattern will determine performance

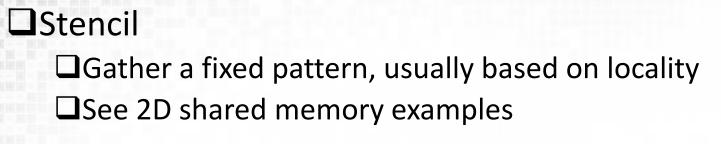


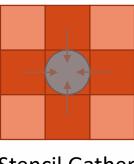
- Scatter operation
- Write to a number of locations
- ☐ Collision on write
- Scatter operation
- ☐ Write to a number of locations
- ☐ Random access write?





#### Other Parallel Patterns





Stencil Gather

#### ☐ Reduce (this lecture)

- ☐ Reduce value to a single value or set of key value pairs
- □Combined with Map to form Map Reduce (often with intermediate shuffle or sort)

#### ☐Scan (this lecture)

- ☐ Compute the sum of previous value in a set
- □Sort (*later*)
  - ☐Sort values or <value, key> pairs



☐ Parallel Patterns Overview

Reduction

■Scan



#### Reduction

- $\square$ A reduction is where **all** elements of a set have a common *binary associative* operator ( $\bigoplus$ ) applied to them to "reduce" the set to a single value
  - ☐ Binary associative = order in which operations is performed on set does not matter
    - $\square$  E.g. (1 + 2) + 3 + 4 == 1 + (2 + 3) + 4 == 10
- ☐ Example operators
  - ☐ Most obvious example is addition (Summation)
  - □Other examples, Maximum, Minimum, product
- ☐ Serial example is trivial but how does this work in parallel?

```
int data[N];
int i, r;
for (int i = 0; i < N; i++) {
   r = reduce(r, data[i]);
}</pre>
```

OR

```
int data[N];
int i, r;
for (int i = N-1; i >= 0; i--){
  r = reduce(r, data[i]);
}
```

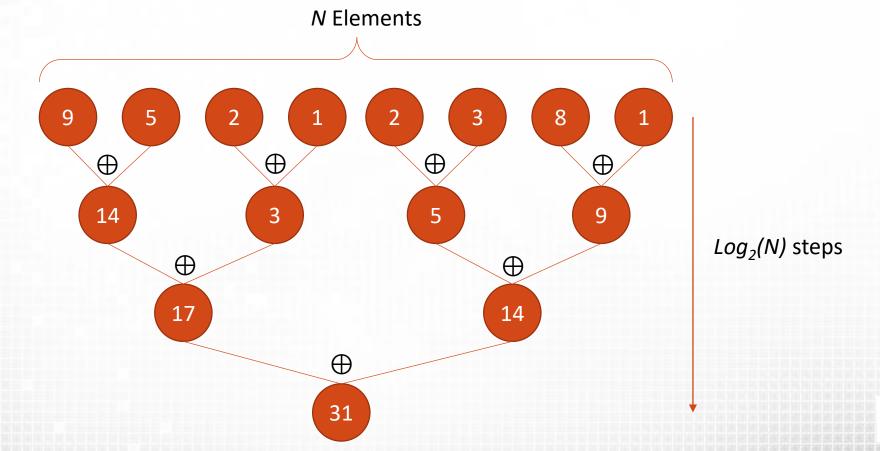
```
int reduce(int r, int i) {
  return r + i;
}
```





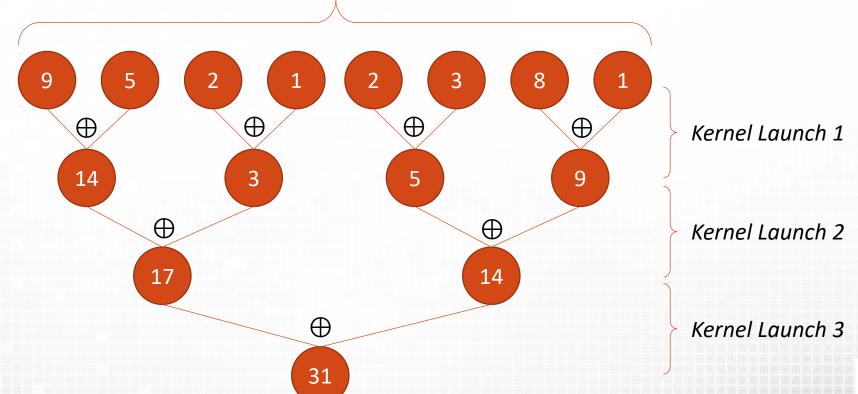
#### Parallel Reduction

- □Order of operations does not matter so we don't have to think serially.
- ☐A tree based approach can be used
  - ☐At each step data is reduced by a factor of 2



#### Parallel Reduction in CUDA

- □No global synchronisation so how do multiple blocks perform reduction?
- ☐ Split the execution into multiple stages
  - ☐ Recursive method











☐ What might be some problems with the following?

```
__global___ void sum_reduction(float *input, float *results) {
    extern __shared__ int sdata[];
    unsigned int i = blockIdx.x*blockDim.x + threadIdx.x;

    sdata[threadIdx.x] = input[i];
    __syncthreads();

    if (i % 2 == 0) {
        results[i / 2] = sdata[threadIdx.x] + sdata[threadIdx.x+1]
    }
}
```





#### Recursive Reduction Problems

☐ High Launch Overhead
 ☐ Lots of reads/writes from global memory
 ☐ Poor use of shared memory or caching
 ☐ Expensive % and / operators
 ☐ Divergent warps

```
__global__ void sum_reduction(float *input, float *results) {
    extern __shared__ int sdata[];
    unsigned int i = blockIdx.x*blockDim.x + threadIdx.x;

    sdata[threadIdx.x] = input[i];
    __syncthreads();

if (i % 2 == 0) {
    results[i / 2] = sdata[threadIdx.x] + sdata[threadIdx.x+1]
    }
}
```





#### Block Level Reduction

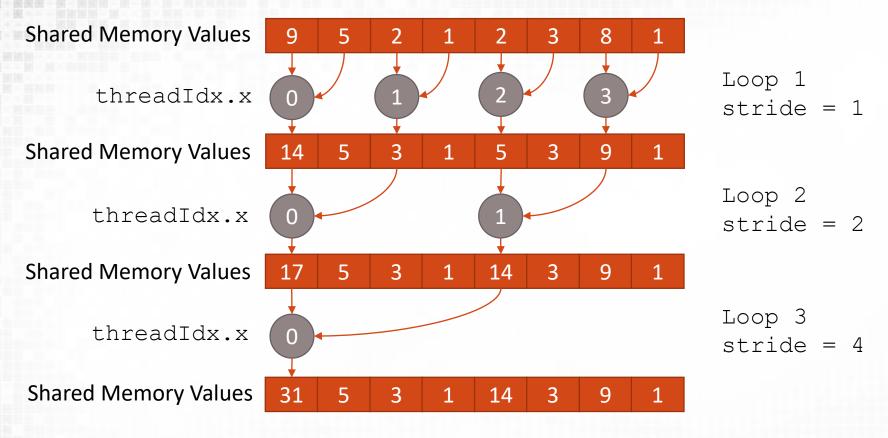
- ☐ Lower launch overhead (reduction within block)
- ☐ Much better use of shared memory

```
global void sum reduction(float *input, float *block results) {
extern shared int sdata[];
unsigned int i = blockIdx.x*blockDim.x + threadIdx.x;
 sdata[threadIdx.x] = input[i];
 syncthreads();
 for (unsigned int stride = 1; stride < blockDim.x; stride*=2) {</pre>
   unsigned int strided i = threadIdx.x * 2 * stride;
   if (strided i < blockDim.x) {</pre>
     sdata[strided i] += sdata[strided i + stride]
    syncthreads();
 if (threadIdx.x == 0)
  block results[blockIdx.x] = sdata[0];
```





#### Block Level Recursive Reduction



```
for (unsigned int stride = 1; stride < blockDim.x; stride*=2) {
  unsigned int strided_i = threadIdx.x * 2 * stride;
  if (strided_i < blockDim.x) {
    sdata[strided_i] += sdata[strided_i + stride]
  }
  __syncthreads();
}</pre>
```









☐ Is this shared memory access pattern bank conflict free?

```
for (unsigned int stride = 1; stride < blockDim.x; stride*=2){
  unsigned int strided_i = threadIdx.x * 2 * stride;
  if (strided_i < blockDim.x){
    sdata[strided_i] += sdata[strided_i + stride]
  }
  __syncthreads();
}</pre>
```





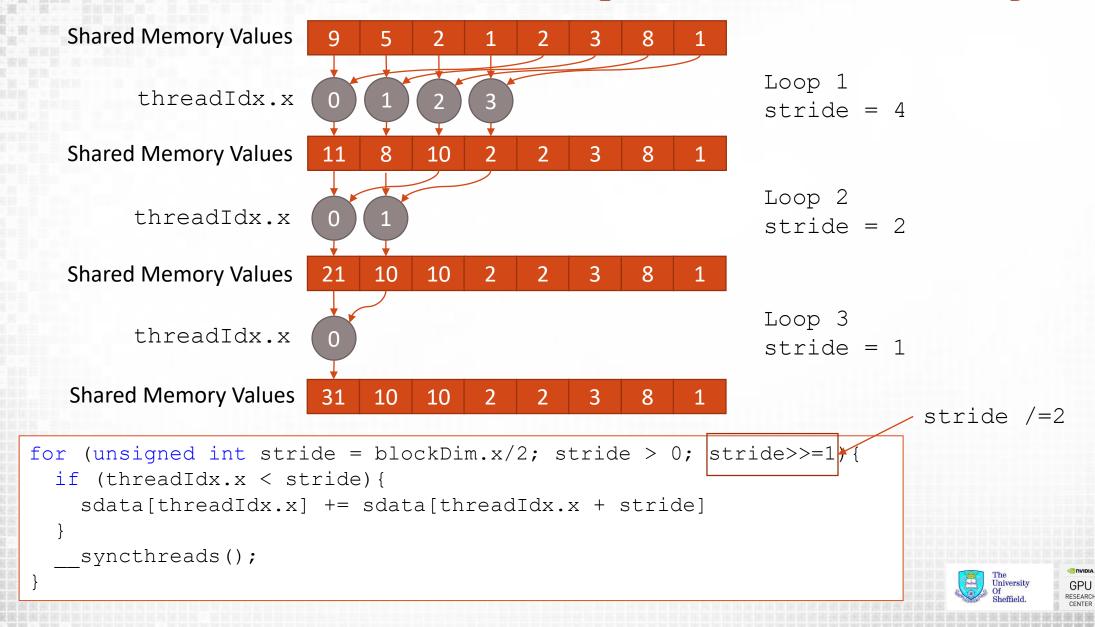
#### Block Level Reduction

- ☐ Is this shared memory access pattern conflict free? No
  - ☐ Each thread accesses SM using the following access pattern
    - Dindex = threadIdx.x \* 2 \* loop\_stride +
      loop stride
  - ☐ Between each thread there is therefore strided access across SM banks
    - ☐ Try evaluating this using a spreadsheet
- ☐ To avoid bank conflicts stride between threads should be 1

```
for (unsigned int stride = 1; stride < blockDim.x; stride*=2) {
  unsigned int strided_i = threadIdx.x * 2 * stride;
  if (strided_i < blockDim.x) {
    sdata[strided_i] += sdata[strided_i + stride]
  }
  __syncthreads();
}</pre>
```

m_stride	1			
oop stride	1			
hreadIdx.x		index	bank	
0		1	1	1
1		3	3	3
2		5		5
3		7		7
4		9	Ç	9
5		11	11	L
6		13	13	3
7		15	15	5
8		17	17	7
9		19	19	Э
10		21	21	l
11		23	23	3
12		25	25	5
13		27	27	7
14		29	29	)
15		31	31	L
16		33	1	L
17		35	3	3
18		37		5
19		39	7	7
20		41	9	9
21		43	11	L
22		45	13	3
23		47	15	5
24		49	17	7
25		51	19	9
26		53	21	1
27		55	23	3
28		57	25	5
29		59	27	7
30		61	29	9
31		63	31	1
				H
		Banks		B
		Used		5
		Max		H
		 Conflicts		2

#### Block Level Reduction (Sequential Addressing)



		dedezedede	
sm_stride	1		
loop stride	1		
threadIdx.x		index	bank
0		1	1
1		2	2
2		3	3
3		4	
4		5	
5		6	
6		7	
7		8	
8		9	
9		10	
10		11	
11		12	
12		13	
13		14	14
14		15	15
15		16	16
16		17	17
17		18	18
18		19	19
19		20	20
20		21	21
21		22	22
22		23	23
23		24	24
24		25	25
25		26	26
26		27	27
27		28	28
28		29	29
29		30	
30		31	
31		32	0
		Banks	
		Used	
		Max	
adar belar belar belar select a construction of		Conflicts	1

- □Now conflict free regardless of the reduction loop stride
- ☐ The stride between shared memory variable accesses for threads is *always* sequential
- ☐ Careful: Two types of stride discussed
- 1. Loop stride (of algorithm)
- 2. SM *variable* stride (in 4 bytes)

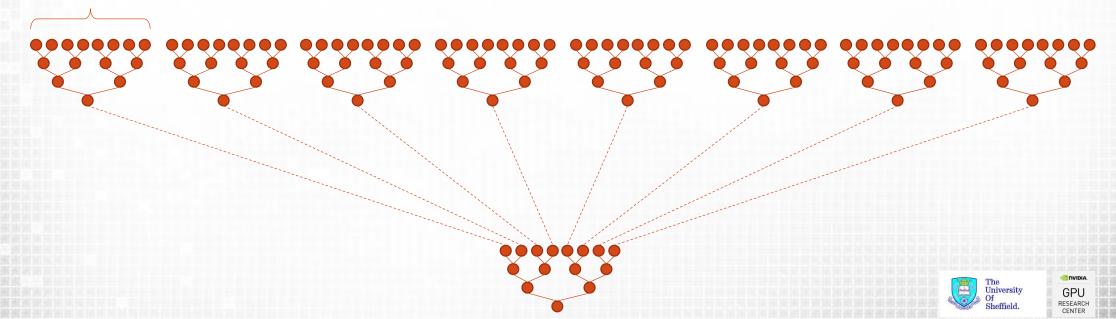




### Global Reduction Approach

- ☐ Use the recursive method
  - ☐Our block level reduction can be applied to the result
  - ☐At some stage it may be more effective to simply sum the final block on the CPU
- Or use atomics on block results

Thread block width



#### Global Reduction Atomics

```
global void sum reduction(float *input, float *result) {
extern shared int sdata[];
unsigned int i = blockIdx.x*blockDim.x + threadIdx.x;
sdata[threadIdx.x] = input[i];
__syncthreads();
for (unsigned int stride = blockDim.x/2; stride > 0; stride>>=2) {
  if (threadIdx.x < stride) {</pre>
    sdata[threadIdx.x] += sdata[threadIdx.x + stride]
   syncthreads();
if (threadIdx.x == 0)
  atomicAdd(result, sdata[0]);
```







#### Further Optimisation?

#### ☐ Can we improve our technique further?

```
global void sum reduction(float *input, float *result) {
extern shared int sdata[];
unsigned int i = blockIdx.x*blockDim.x + threadIdx.x;
sdata[threadIdx.x] = input[i];
syncthreads();
for (unsigned int stride = blockDim.x/2; stride > 0; stride>>=2) {
  if (threadIdx.x < stride) {</pre>
    sdata[threadIdx.x] += sdata[threadIdx.x + stride]
    syncthreads();
if (threadIdx.x == 0)
  atomicAdd(result, sdata[0]);
```





#### Further Optimisation?

☐ Can we improve our technique further? Yes

#### **☐** We could optimise for the warp level

- □ Warp Level: Shuffles for reduction (see last lecture)
- ☐ Thread Block Level: Shared Memory reduction (or Maxwell SM atomics)
- ☐ Grid Block Level: Recursive Kernel Launches or Global Atomics

#### □Other optimisations

- □ Loop unrolling
- ☐ Increasing Thread Level Parallelism

□ Different architectures may favour different implementations/optimisations



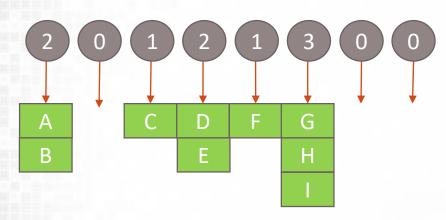


☐ Parallel Patterns Overview☐ Reduction

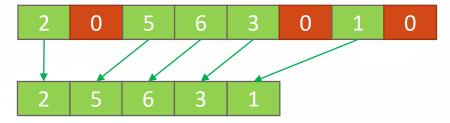


#### What is scan?

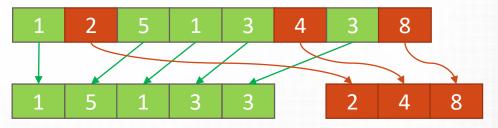
☐ Consider the following ...



Output variable numbers of values per thread



Remove empty elements from array (compact)



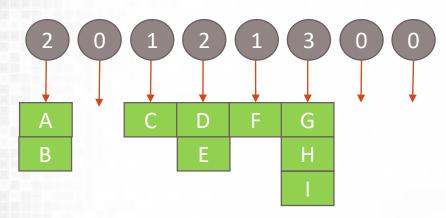
Split elements from array based on condition (split)





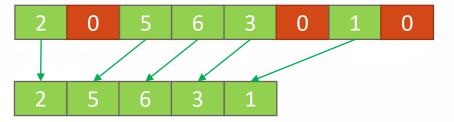
#### What is scan?

□Consider the following ...

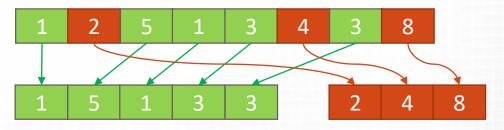


Output variable numbers of values per thread

- ☐ Each has the same problem ☐ Not even considered for sequential programs!
- ☐ Where to write output in parallel?



Remove empty elements from array (compact)



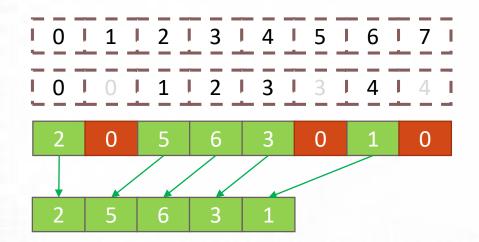
Split elements from array based on condition (split)





#### Parallel Prefix Sum (scan)

- ☐ Where to write output in parallel?
  - ☐ Each threads needs to know the output location(s) it can write to avoid conflicts.



Thread/Read index

Output/Write index – running sum of binary output state

Sparse data

Compacted data

- ☐ The solution is a parallel prefix sum (or scan)
  - $\square$  Given the inputs  $A = [a_0, a_1, ..., a_{n-1}]$  and binary associate operator  $\bigoplus$
  - $\square Scan(A) = [0, a0, (a_0 \oplus a_1), ..., (a_0 \oplus a_1 \oplus ... \oplus a_{n-1})]$





#### Serial Parallel Prefix Sum Example

☐ E.g. Given the input and the addition operator

```
\square A = [2, 6, 2, 4, 7, 2, 1, 5]
\square Scan(A) = [0, 2, 2+6, 2+6+2, 2+6+2+4, ...]
\square Scan(A) = [0, 2, 8, 10, 14, 21, 23, 24]
```

☐ More generally a serial implementation of an additive scan using a running sum looks like...

```
int A[8] = { 2, 6, 2, 4, 7, 2, 1, 5 };
int scan_A[8];
int running_sum = 0;
for (int i = 0; i < 8; ++i)
{
   scan_A[i] = running_sum;
   running_sum += A[i];
}</pre>
```



#### Serial Scan for Compaction

```
int Input[8] = { 2, 0, 5, 6, 3, 0, 1, 0 };
int A[8] = \{ 2, 0, 5, 6, 3, 0, 1, 0 \};
int scan A[8];
int output[5]
int running sum = 0;
for (int i = 0; i < 8; ++i) {
 A[i] = Input > 0;
for (int i = 0; i < 8; ++i) {
 scan A[i] = running sum;
 running sum += A[i];
for (int i = 0; i < 8; ++i) {
  int input = Input[i];
  if (input > 0) {
   int idx = scan A[i];
   output[idx] = input;
```

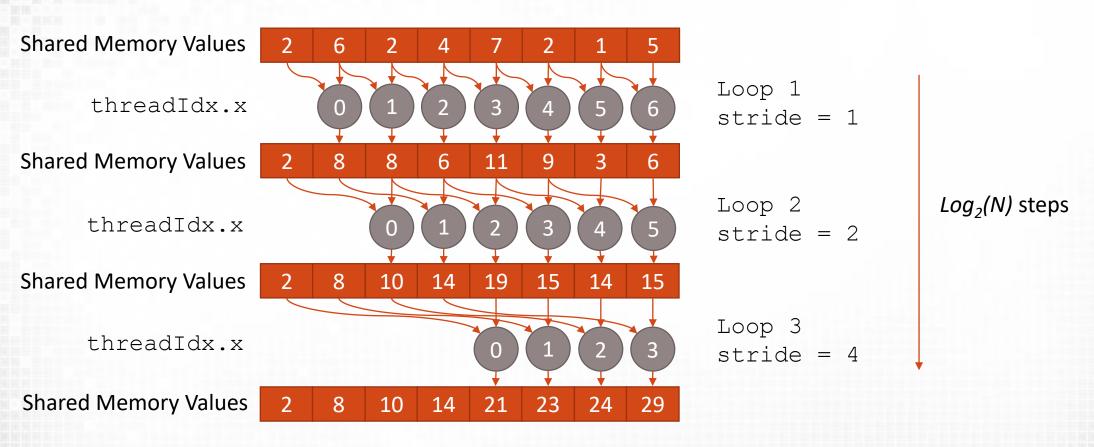
```
// generate scan input
// A = {1, 0, 1, 1, 1, 0, 1, 0}
// scan
// \text{ result} = \{0, 1, 1, 2, 3, 4, 4, 5\}
// scattered write
// output = {2, 5, 6, 3, 1}
```





#### Parallel Local (Shared Memory) Scan

After Log(N) loops each sum has local plus preceding  $2^{n}-1$  values

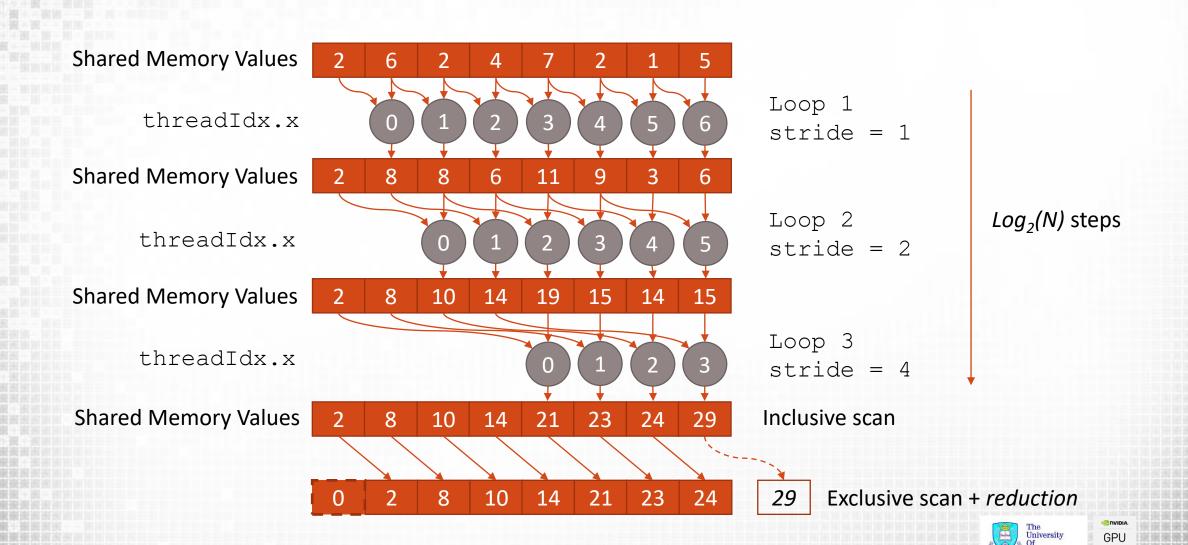


**Inclusive Scan** 





#### Parallel Local Scan



#### Implementing Local Scan with Shared Memory

```
__global___ void scan(float *input) {
    extern __shared__ float s_data[];
    s_data[threadIdx.x] = input[threadIdx.x + blockIdx.x*blockDim.x];

for (int stride = 1; stride<blockDim.x; stride<<=1) {
        __syncthreads();
        float s_value = (threadIdx.x >= stride) ? s_data[threadIdx.x - stride] : 0;
        __syncthreads();
        s_data[threadIdx.x] += s_value;
}

//something with global results?
}
```

- ■No bank conflicts (stride of 1 between threads)
- ☐ Synchronisation required between read and write





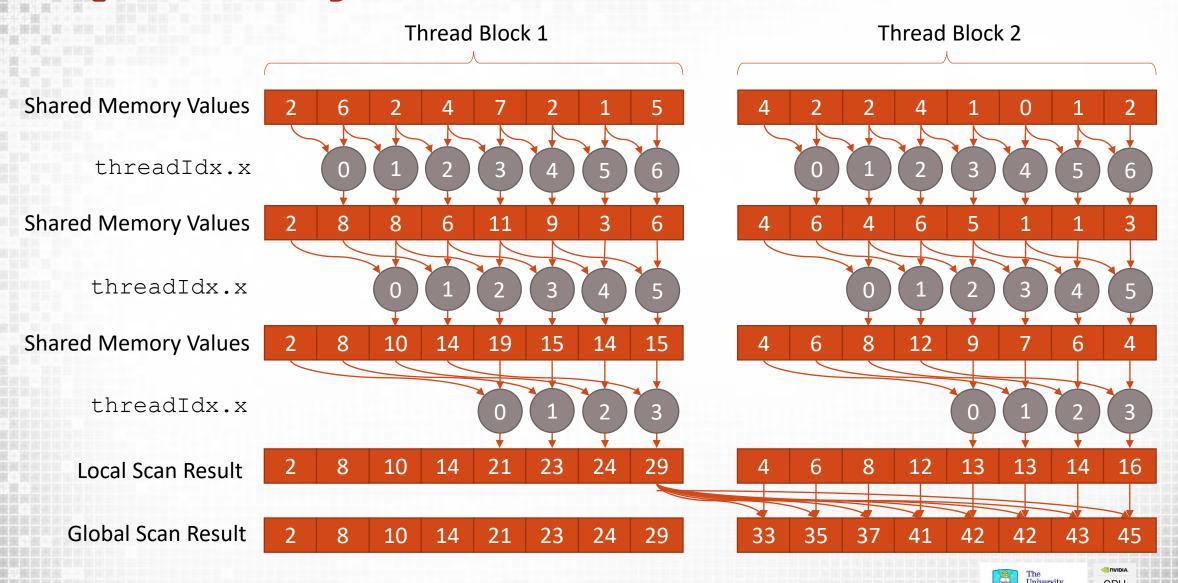
#### Implementing Local Scan (at warp level)

- ☐ Exactly the same as the block level technique but at warp level
- □Warp prefix sum is in threadIdx.x%32==31
- ☐ Either use shared memory to reduce between warps
  - ☐ Or consider the following global scan approaches.





#### Implementing scan at Grid Level



#### Implementing scan at Grid Level

- ☐Same problem as reduction when scaling to grid level
  - ☐ Each block is required to add the reduction value from proceeding blocks
- □Global scan therefore requires either;
  - 1. Recursive scan kernel on results of local scan
    - ☐ Additional kernel to add sums of proceeding blocks
  - 2. Atomic Increments (next slides)
    - ☐ Increment a counter for block level results
    - ☐ Additional kernel to add sums of proceeding blocks to each value



#### Global Level Scan (Atomics Part 1)

```
device block sums[GRID DIM];
global void scan(float *input, float *local result) {
 extern shared float s data[];
 s data[threadIdx.x] = input[threadIdx.x + blockIdx.x*blockDim.x];
 for (int stride = 1; stride < blockDim.x; stride < <=1) {</pre>
   __syncthreads();
   float s value = (threadIdx.x >= stride) ? s data[threadIdx.x - stride] : 0;
   __syncthreads();
   s data[threadIdx.x] += s value;
 //store local scan result to each thread
 local_result[threadIdx.x + blockIdx.x*blockDim.x] = s data[threadIdx.x];
 //atomic store to all proceeding block totals
 if (threadIdx.x == 0) {
   for (int i=0; i<blockIdx.x; i++)</pre>
     atomicAdd(&block sums[i], s data[blockDim.x-1]);
```

#### Global Level Scan (Atomics Part 2)

□ After completion of the first kernel, block sums are all synchronised □ Use first thread in block to load block total into shared memory □ Increment local result

```
__device__ block_sums[BLOCK_DIM];

__global__ void scan_update(float *local_result, float *global_result) {
    extern __shared__ float block_total;
    int idx = threadIdx.x + blockIdx.x*blockDim.x;

    if (threadIdx.x == 0)
        block_total = block_sums[blockIdx.x];

    __syncthreads();

    global_result[idx] = local_result[idx]+block_total;
}
```





Summa	ry	
	el Patterns create a bottom up model for constructing hms from parallel building blocks	
	tion can be implemented recursively however re-use of data ostly memory movement operations	
	a building block for all kinds of problems be used for compaction and split	
Paralle levels.	el patterns can be optimised at warp, thread block and grid	
	cs can be used in the reduction or scan value summation en blocks or warps	
	f potential techniques to implement and evaluate unately in many cases libraries and examples already exist	



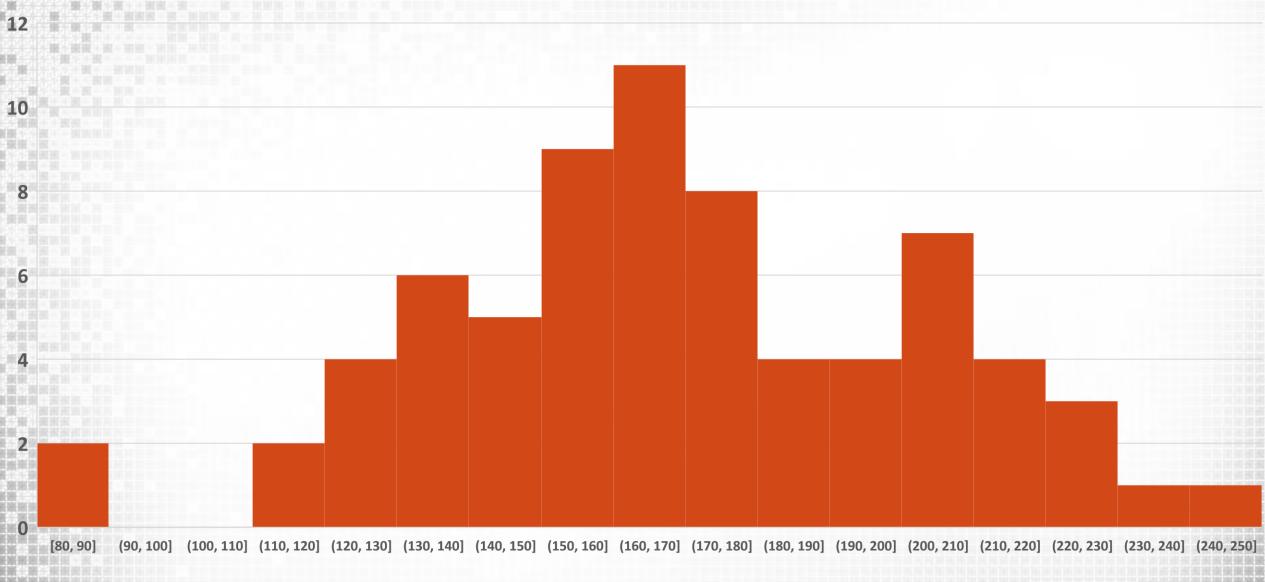


#### Acknowledgements and Further Reading

- https://devblogs.nvidia.com/parallelforall/faster-parallel-reductionskepler/
  - □All about application of warp shuffles to reduction
- https://stanford-cs193gsp2010.googlecode.com/svn/trunk/lectures/lecture 6/parallel patte rns 1.ppt
  - ☐Scan material based loosely on this lecture
- http://docs.nvidia.com/cuda/samples/6 Advanced/reduction/doc/reduction.pdf
  - ☐ Reduction material is based on this fantastic lecture by Mark Harris (NVIDIA)











#### PhD Position

- ☐ Interested in doing PhD?
- ☐ Title: Parallel computation of adaptive wavelet-based 2D

flood models

- □Supervisors: Georges Kesserwani, Paul Richmond
- □ Deadline: July 1<sup>st</sup>, 2019

#### Apply here:

http://tinyurl.com/y3fw5n8r



