King Abdullah University of Science and Technology KAUST

CS 380 - GPU and GPGPU Programming
Lecture 19: GPU Parallel Prefix Sum, Pt. 2; GPU Texturing, Pt. 1

Markus Hadwiger, KAUST

Reading Assignment #11 (until Nov 17)

Read (required):

- Interpolation for Polygon Texture Mapping and Shading, Paul Heckbert and Henry Moreton

  `https://www.ri.cmu.edu/publications/interpolation-for-polygon-texture-mapping-and-shading/`

- Homogeneous Coordinates

  `https://en.wikipedia.org/wiki/Homogeneous_coordinates`

Read (optional; highly recommended!):

- MIP-Map Level Selection for Texture Mapping

  `https://ieeexplore.ieee.org/stamp/stamp.jsp?arnumber=765326`

Next Lectures

Lecture 20: Thu, Nov 13

Lecture 21: Mon, Nov 17 (Quiz #2)

Lecture 22: Tue, Nov 18 (make-up lecture; 14:30 – 16:00, room 3131)

Lecture 23: Thu, Nov 20

Quiz #2: Oct 17

Organization

- First 30 min of lecture
- No material (book, notes, ...) allowed

Content of questions

- Lectures (both actual lectures and slides)
- Reading assignments
- Programming assignments (algorithms, methods)
- Solve short practical examples

GPU Parallel Prefix Sum

- Basic parallel programming primitive; parallelize inherently sequential operations

Parallel Prefix Sum (Scan)

- **Definition:**

  The all-prefix-sums operation takes a binary associative operator $\oplus$ with identity I, and an array of n elements

  $$[a_0, a_1, \ldots, a_{n-1}]$$

  and returns the ordered set

  $$[I, a_0, (a_0 \oplus a_1), \ldots, (a_0 \oplus a_1 \oplus \ldots \oplus a_{n-2})].$$

Exclusive scan: last input element is not included in the result

- **Example:**
  if $\oplus$ is addition, then scan on the set

  [3 1 7 0 4 1 6 3]

  returns the set

  [0 3 4 11 11 15 16 22]

(From Blelloch, 1990, "Prefix Sums and Their Applications)

Work Efficiency

Guy E. Blelloch and Bruce M. Maggs:
Parallel Algorithms, 2004 (https://www.cs.cmu.edu/~guyb/papers/BM04.pdf)

In designing a parallel algorithm, it is more important to make it efficient than to make it asymptotically fast. The efficiency of an algorithm is determined by the total number of operations, or work that it performs. On a sequential machine, an algorithm's work is the same as its time. On a parallel machine, the work is simply the processor-time product. Hence, an algorithm that takes time t on a P-processor machine performs work W = Pt. In either case, the work roughly captures the actual cost to perform the computation, assuming that the cost of a parallel machine is proportional to the number of processors in the machine.

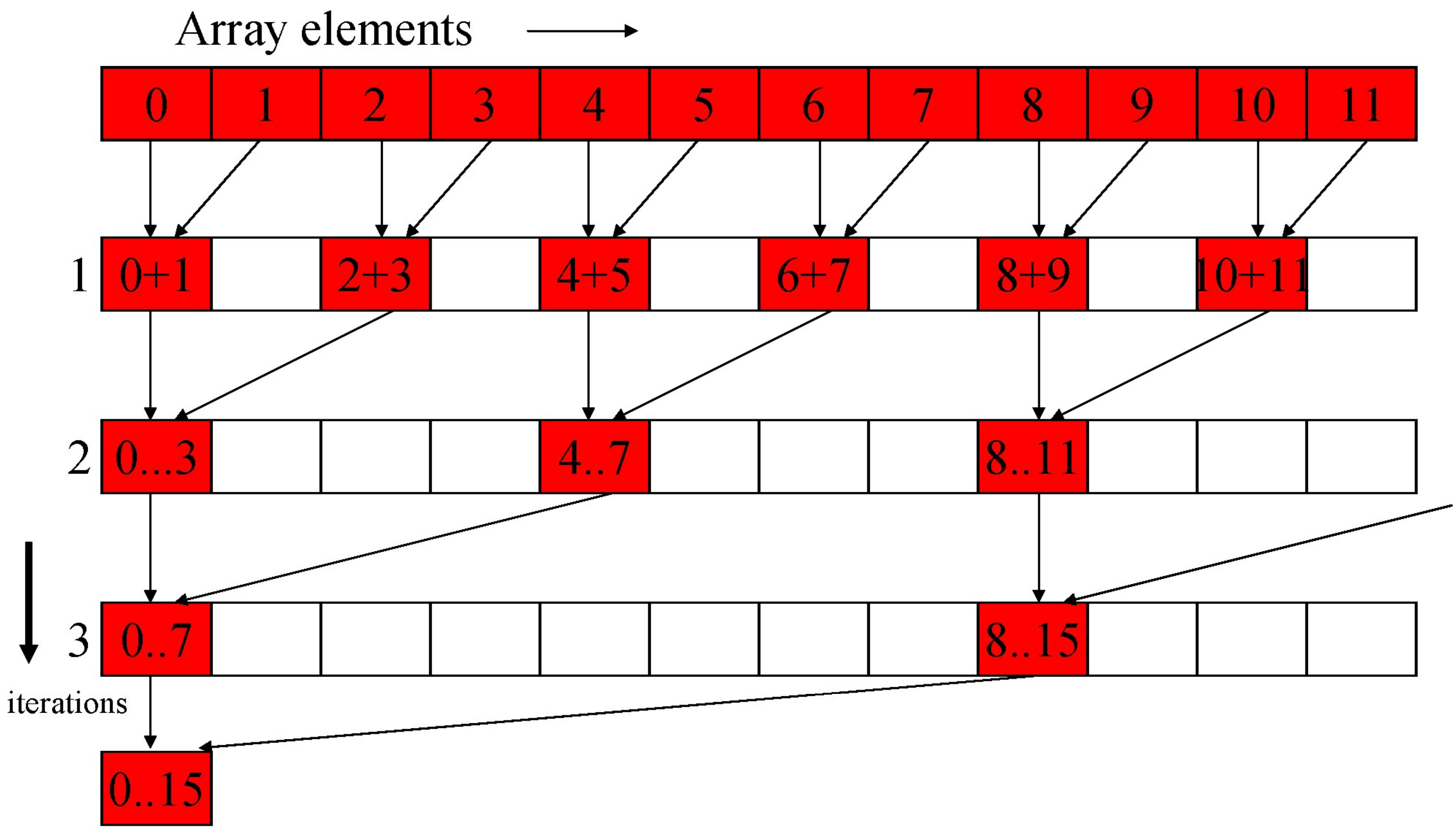
We call an algorithm work-efficient (or just efficient) if it performs the same amount of work, to within a constant factor, as the fastest known sequential algorithm.

For example, a parallel algorithm that sorts n keys in O(sqrt(n) log(n)) time using sqrt(n) processors is efficient since the work, O(n log(n)), is as good as any (comparison-based) sequential algorithm.

However, a sorting algorithm that runs in O(log(n)) time using n^2 processors is not efficient.

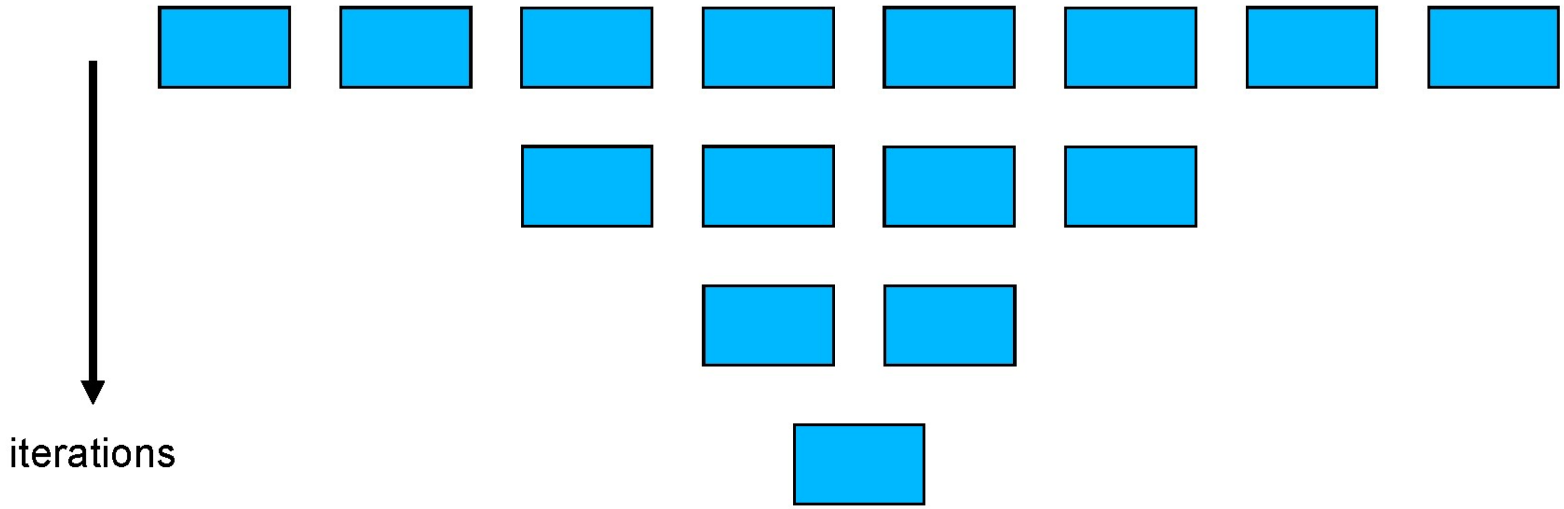
The first algorithm is better than the second - even though it is slower - because its work, or cost, is smaller. Of course, given two parallel algorithms that perform the same amount of work, the faster one is generally better.

Vector Reduction



Typical Parallel Programming Pattern

- **log(n) steps**

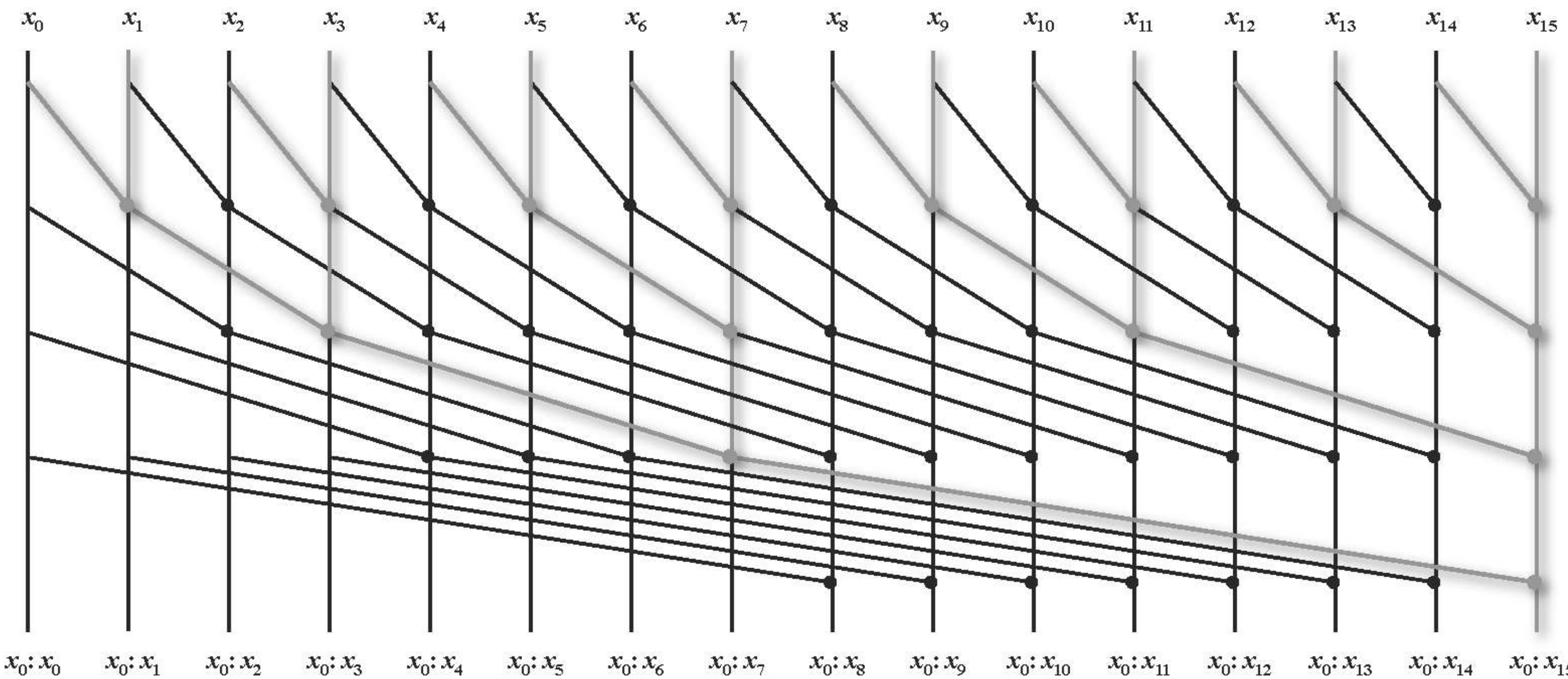


Helpful fact for counting nodes of full binary trees:
If there are N leaf nodes, there will be N-1 non-leaf nodes

Courtesy John Owens

Kogge-Stone Scan

Circuit family

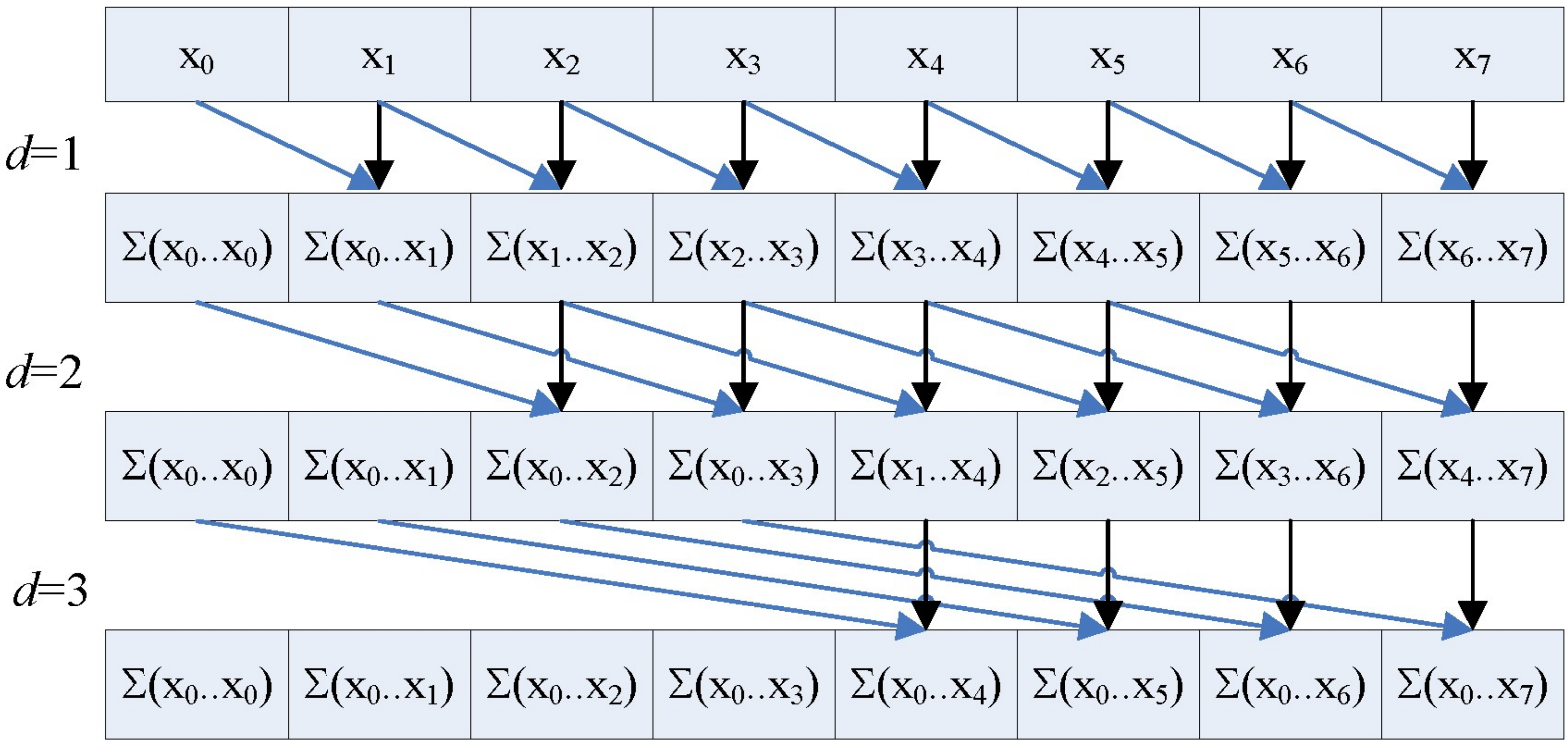


A Parallel Algorithm for the Efficient Solution of a General Class of Recurrence Equations, Kogge and Stone, 1973

See “carry lookahead” adders vs. “ripple carry” adders

$O(n \log n)$ Scan

Courtesy John Owens

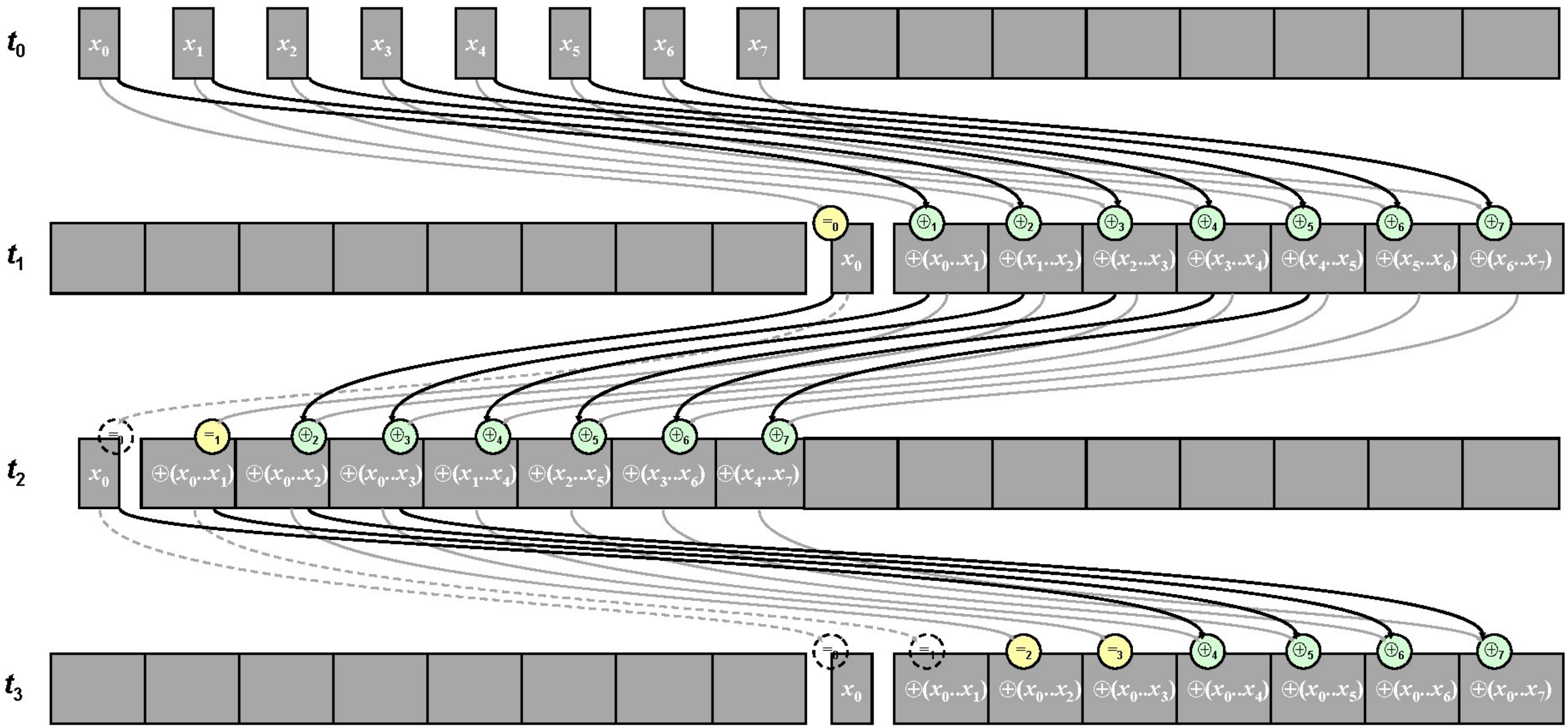


- Step efficient (log *n* steps)
- Not work efficient (*n* log *n* work)
- Requires barriers at each step (WAR dependencies)

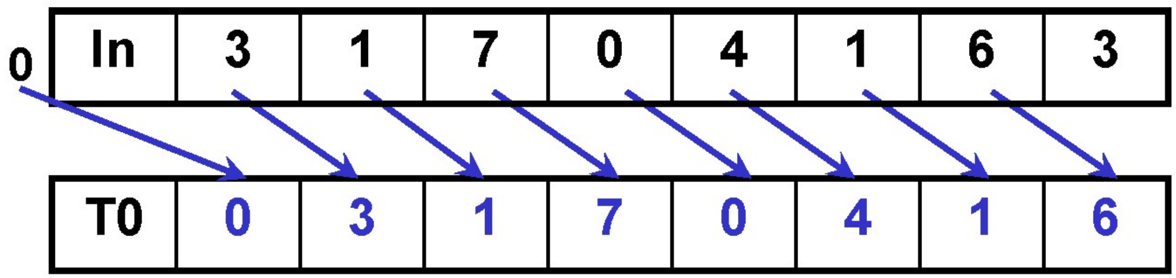
Courtesy John Owens

Hillis-Steele Scan Implementation

No WAR conflicts, $O(2N)$ storage



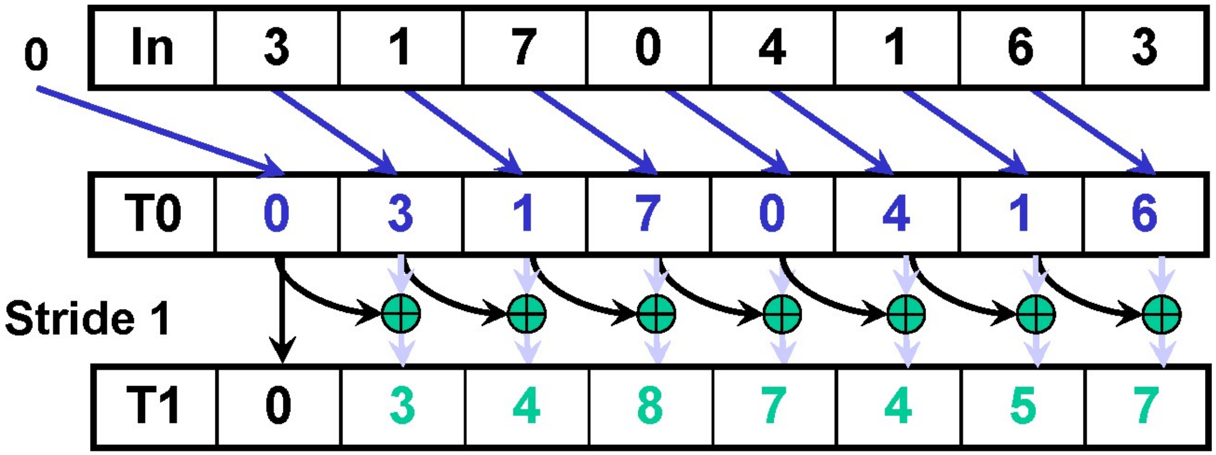
A First-Attempt Parallel Scan Algorithm



Each thread reads one value from the input array in device memory into shared memory array T0. Thread 0 writes 0 into shared memory array.

1. Read input from device memory to shared memory. Set first element to zero and shift others right by one.

A First-Attempt Parallel Scan Algorithm

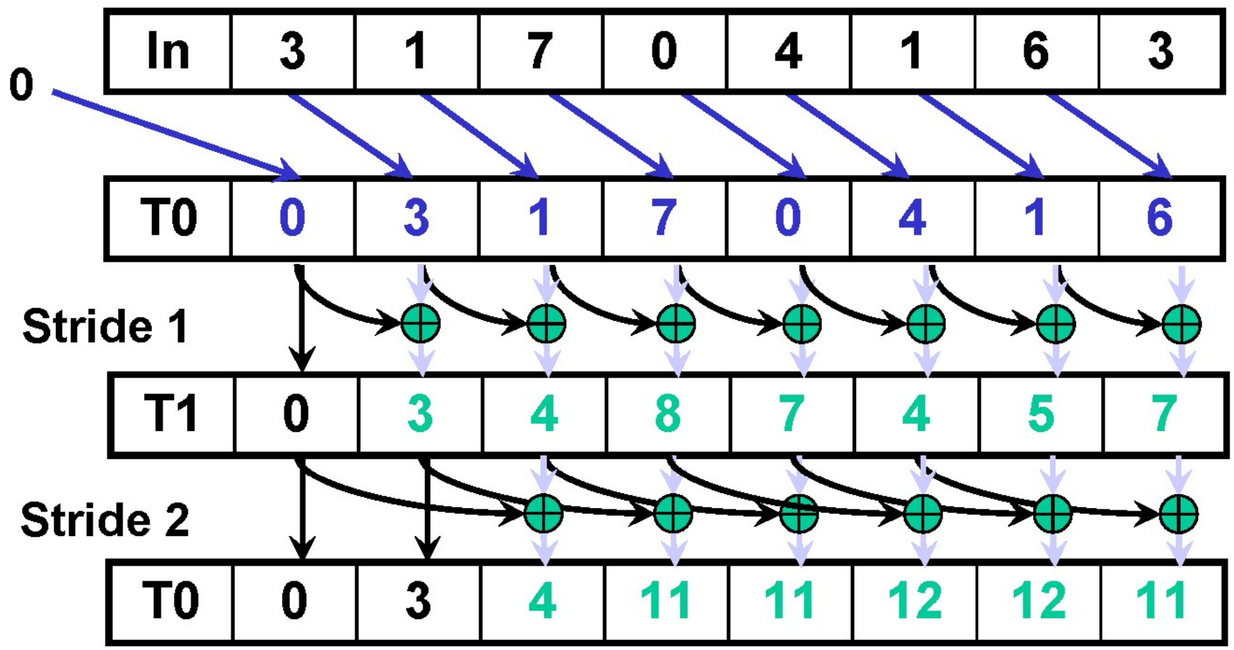


1. (previous slide)
2. Iterate log(n) times: Threads *stride* to *n:* Add pairs of elements *stride* elements apart. Double *stride* at each iteration. (note must double buffer shared mem arrays)

Iteration #1
Stride = 1

- Active threads: *stride* to *n*-1 (*n-stride* threads)
- Thread *j* adds elements *j* and *j-stride* from T0 and writes result into shared memory buffer T1 (ping-pong)

A First-Attempt Parallel Scan Algorithm

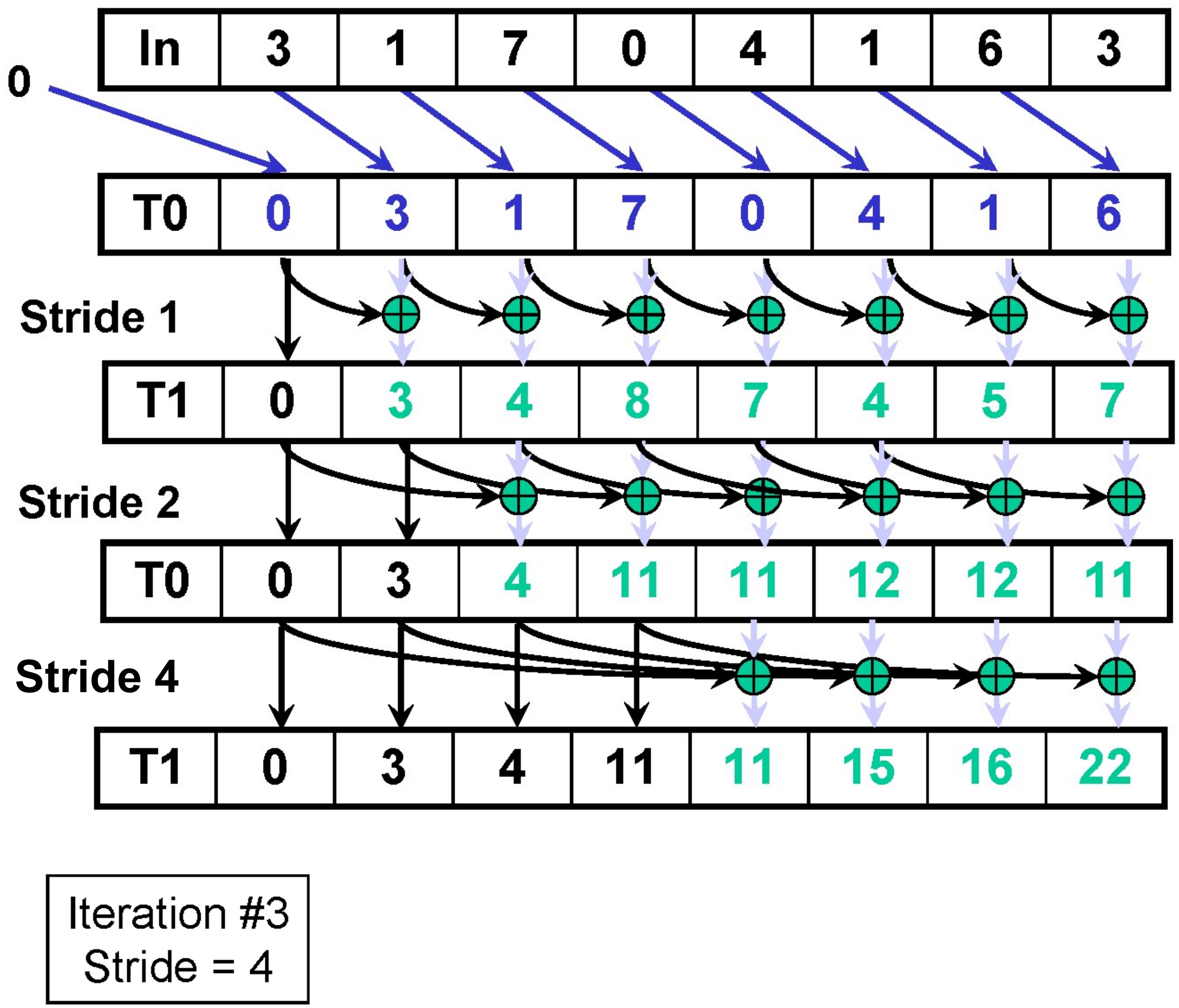


1. Read input from device memory to shared memory. Set first element to zero and shift others right by one.

2. Iterate log(n) times: Threads *stride* to *n:* Add pairs of elements *stride* elements apart. Double *stride* at each iteration. (note must double buffer shared mem arrays)

Iteration #2
Stride = 2

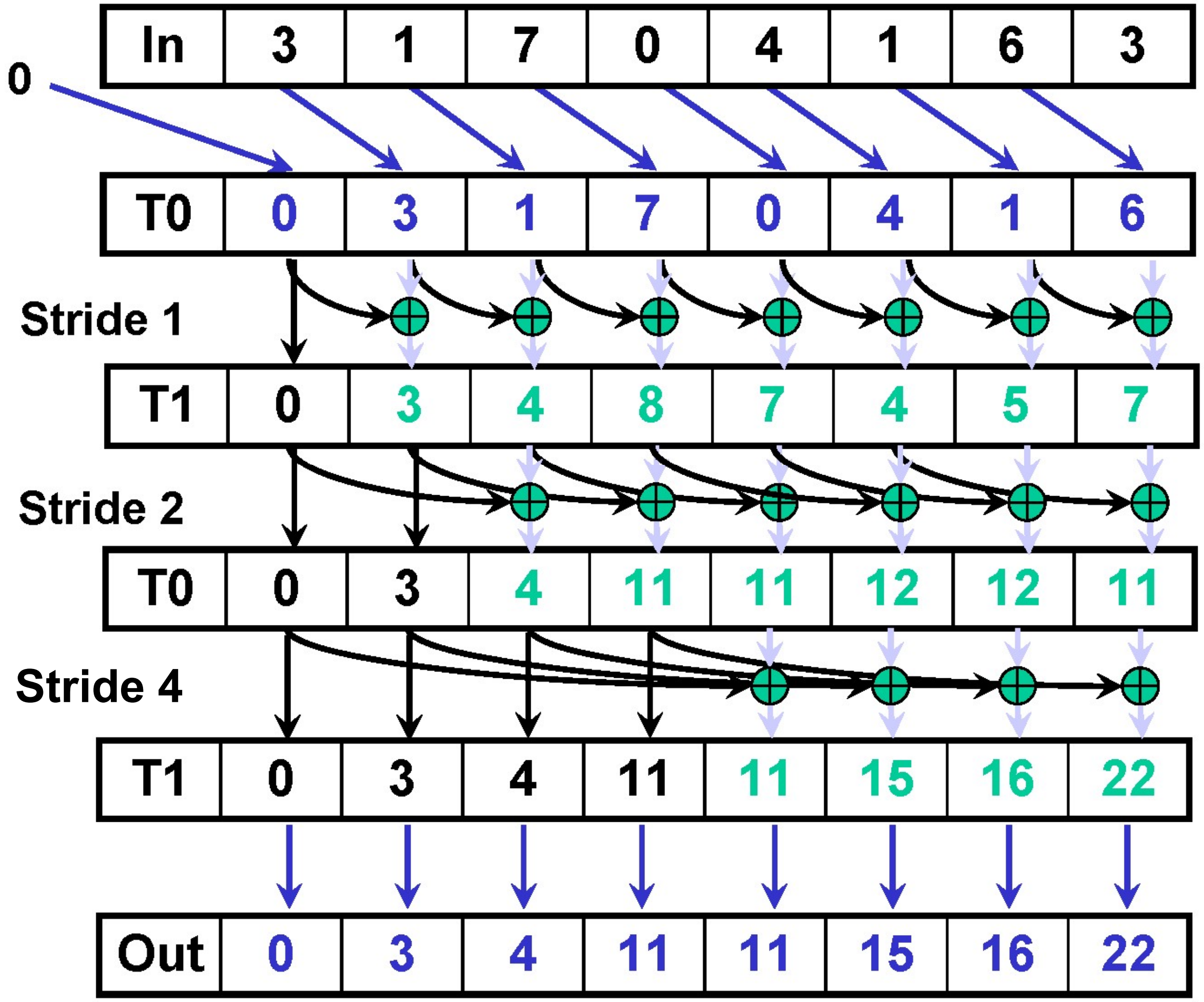
A First-Attempt Parallel Scan Algorithm



1. Read input from device memory to shared memory. Set first element to zero and shift others right by one.

2. Iterate log(n) times: Threads *stride* to *n:* Add pairs of elements *stride* elements apart. Double *stride* at each iteration. (note must double buffer shared mem arrays)

A First-Attempt Parallel Scan Algorithm



1. Read input from device memory to shared memory. Set first element to zero and shift others right by one.
2. Iterate log(n) times: Threads *stride* to *n:* Add pairs of elements *stride* elements apart. Double *stride* at each iteration. (note must double buffer shared mem arrays)
3. Write output to device memory.

Work Efficiency Considerations

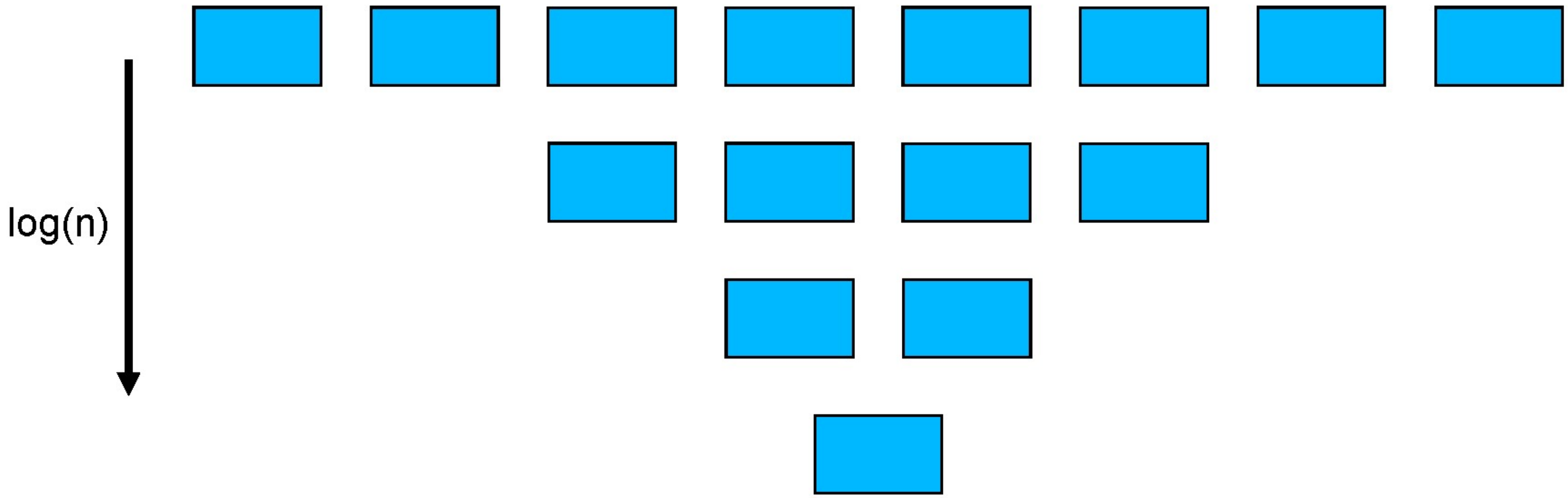
- **The first-attempt Scan executes log(n) parallel iterations**
  - Total adds: n * (log(n) – 1) + 1 → O(n*log(n)) work
- **This scan algorithm is not very work efficient**
  - Sequential scan algorithm does *n* adds
  - A factor of log(n) hurts: 20x for 10^6 elements!
- **A parallel algorithm can be slow when execution resources are saturated due to low work efficiency**

Balanced Trees

- **For improving efficiency**
- **A common parallel algorithm pattern:**
  - Build a balanced binary tree on the input data and sweep it to and from the root
  - Tree is not an actual data structure, but a concept to determine what each thread does at each step
- **For scan:**
  - Traverse down from leaves to root building partial sums at internal nodes in the tree
    - Root holds sum of all leaves
  - Traverse back up the tree building the scan from the partial sums

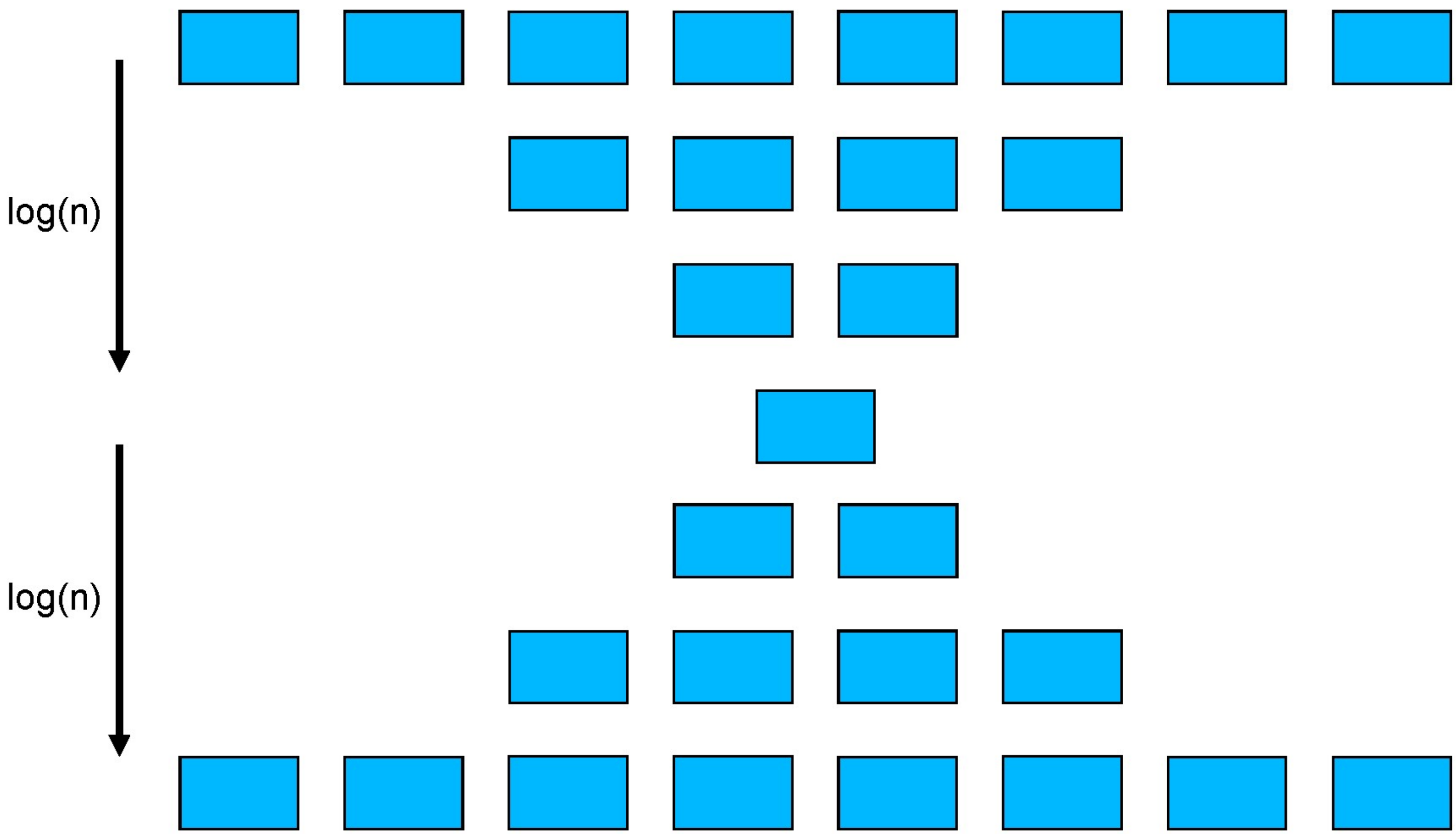
Typical Parallel Programming Pattern

- **2 log(n) steps**



Typical Parallel Programming Pattern

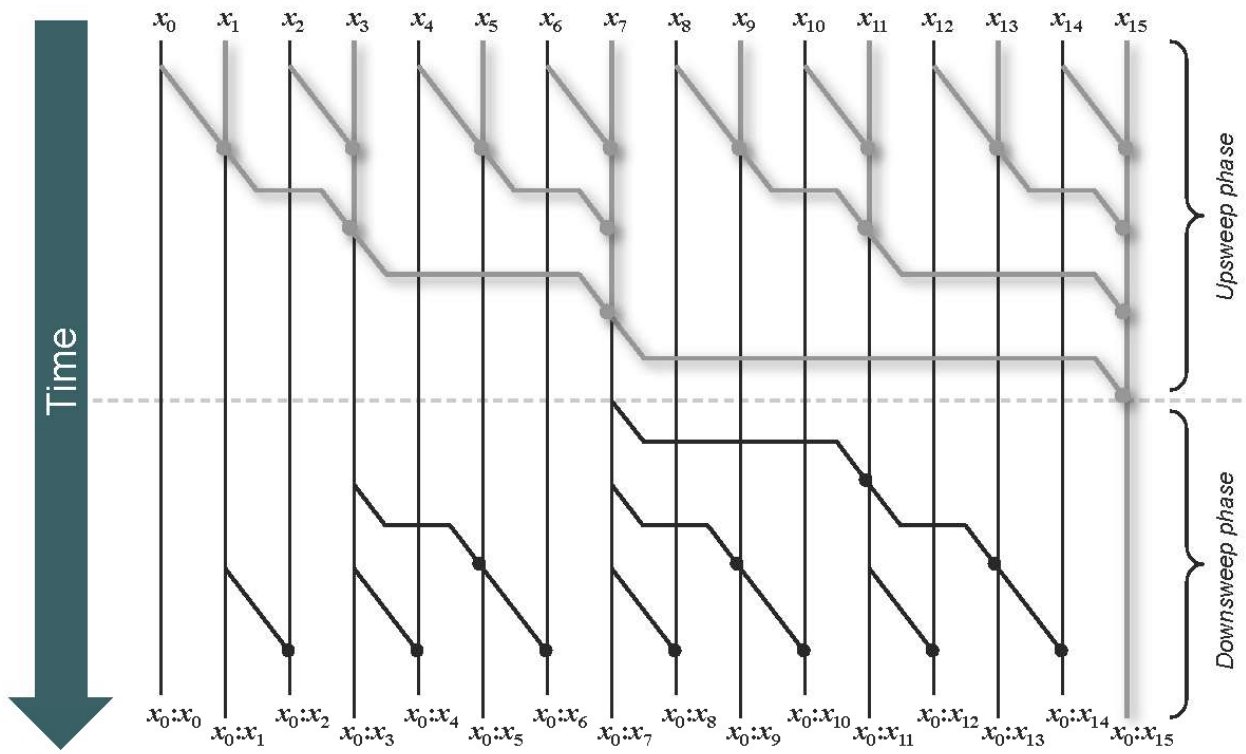
- **2 log(n) steps**



Courtesy John Owens

Brent Kung Scan

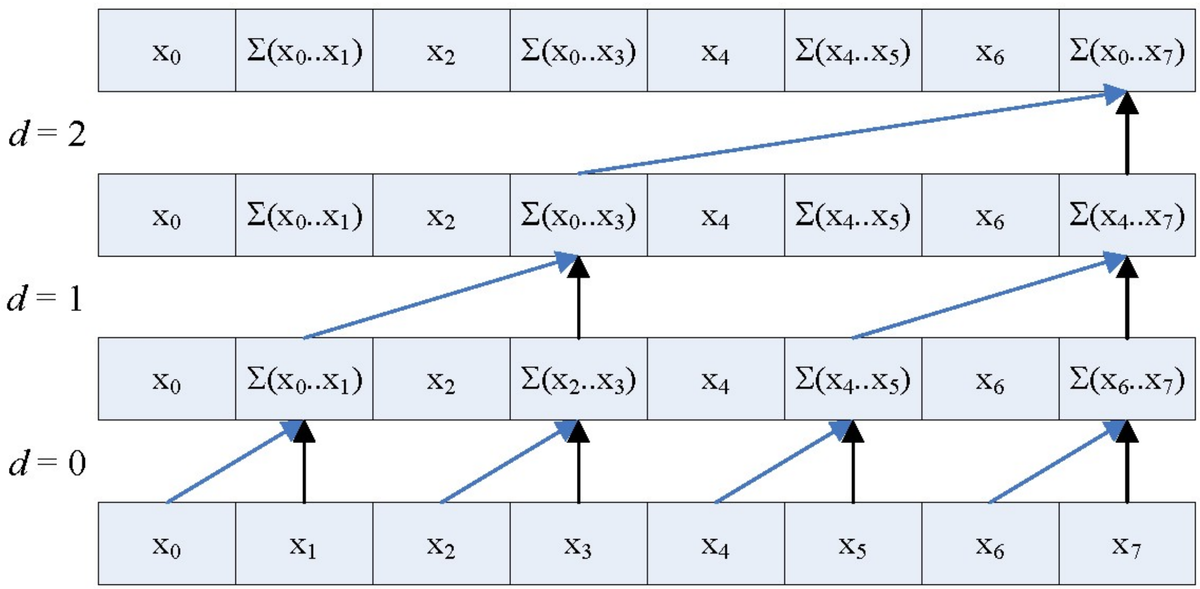
Circuit family

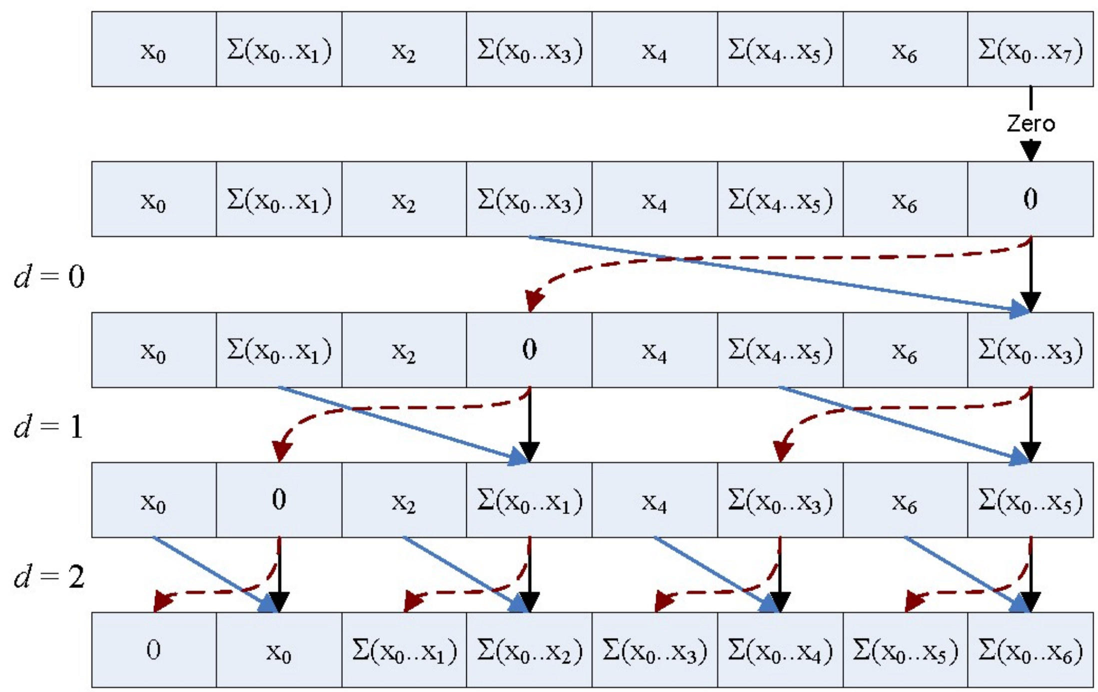


A Regular Layout for Parallel Adders, Brent and Kung, 1982

$O(n)$ Scan [Blelloch]

Courtesy John Owens





- Work efficient ($O(n)$ work)
- Bank conflicts, and lots of 'em

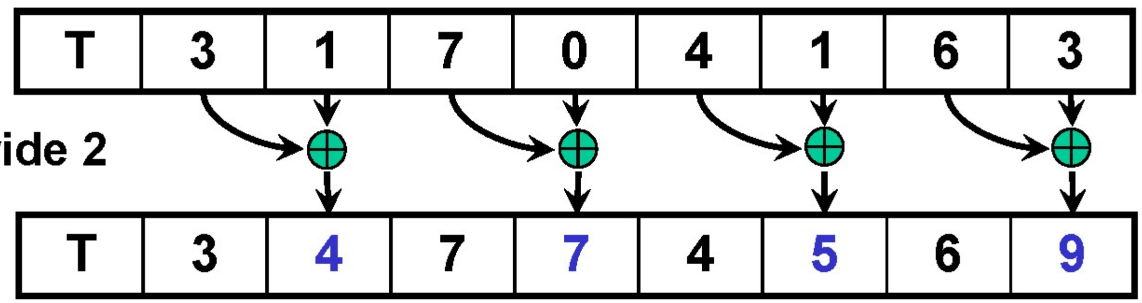
Build the Sum Tree

T	3	1	7	0	4	1	6	3

Assume array is already in shared memory

Build the Sum Tree

Stride 2

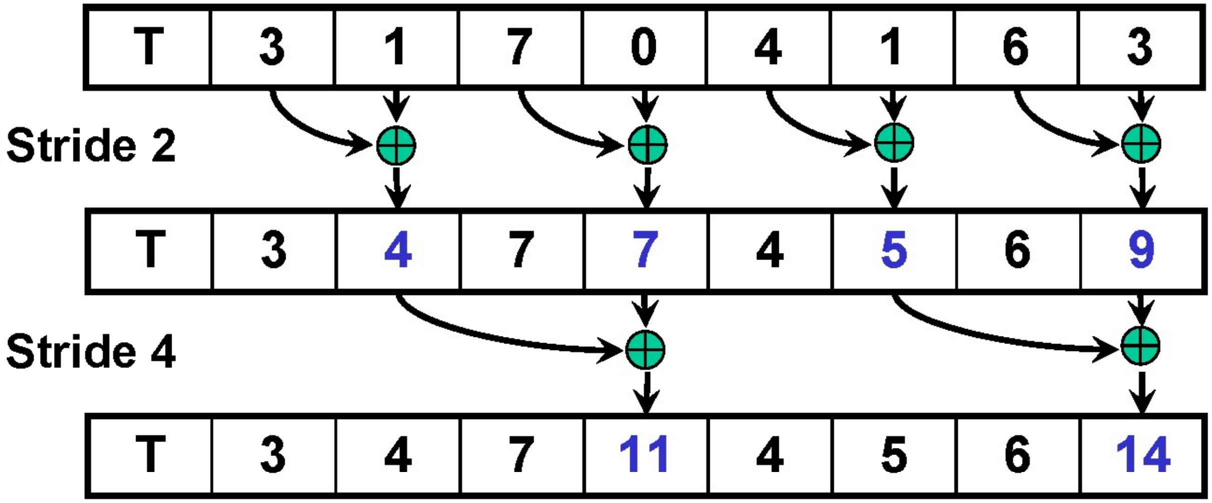


Iteration 1, *n*/2 threads

Each $\oplus$ corresponds to a single thread.

Iterate log(n) times. Each thread adds value *stride* / 2 elements away to its own value.

Build the Sum Tree

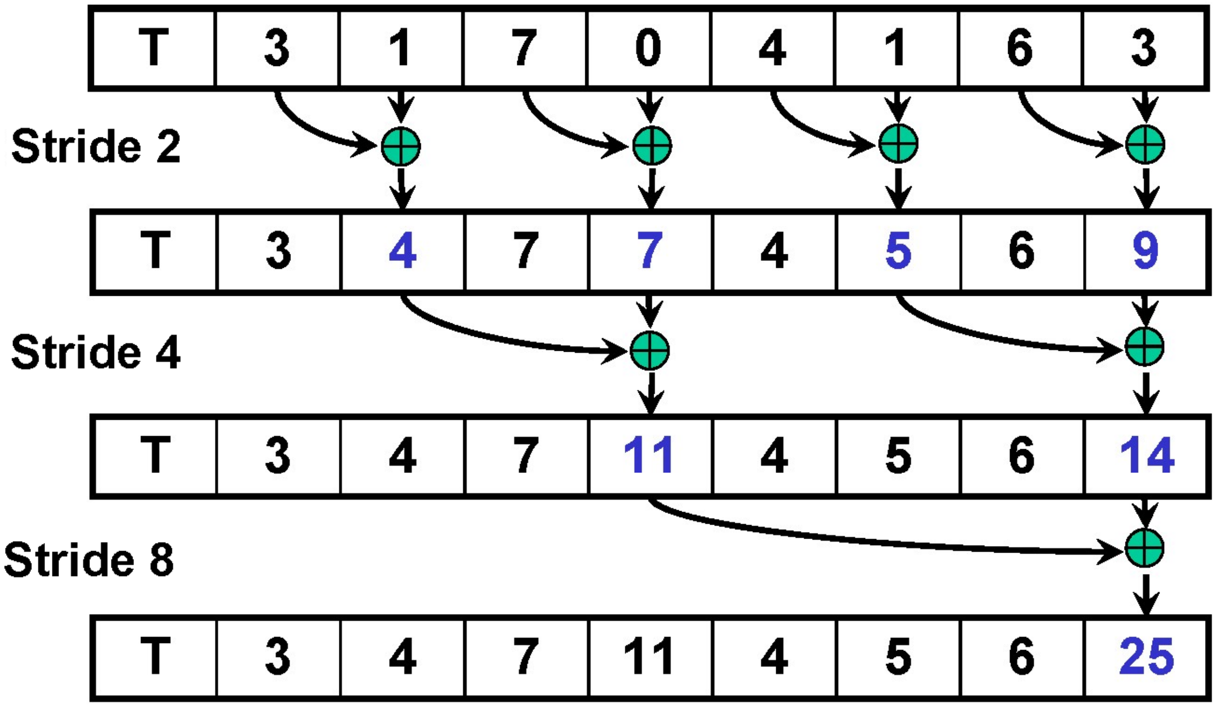


Iteration 2, *n*/4 threads

Each ⊕ corresponds to a single thread.

Iterate log(n) times. Each thread adds value *stride / 2* elements away to its own value.

Build the Sum Tree



Iteration log(*n*), 1 thread

Each ⊕ corresponds to a single thread.

Iterate log(n) times. Each thread adds value *stride* / 2 elements away to its own value.

Note that this algorithm operates in-place: no need for double buffering

Down-Sweep Variant 1: Exclusive Scan

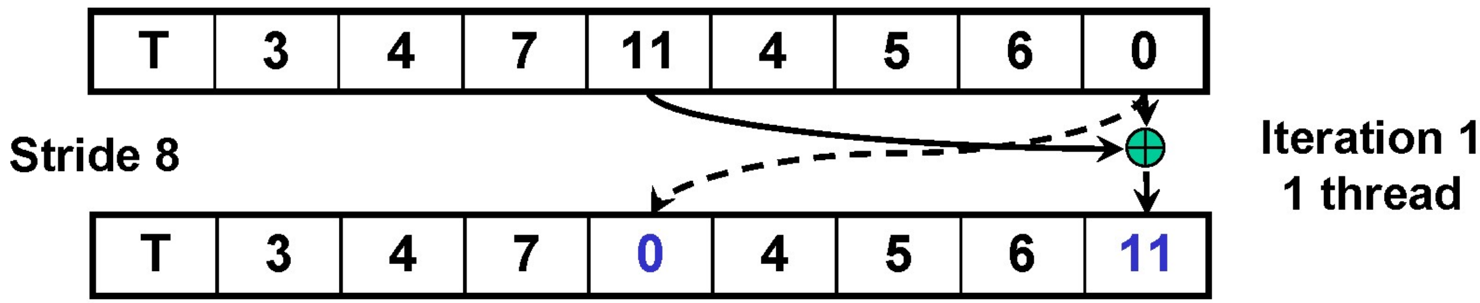
T	3	4	7	11	4	5	6	0

We now have an array of partial sums. Since this is an exclusive scan, set the last element to zero. It will propagate back to the first element.

Build Scan From Partial Sums

T	3	4	7	11	4	5	6	0

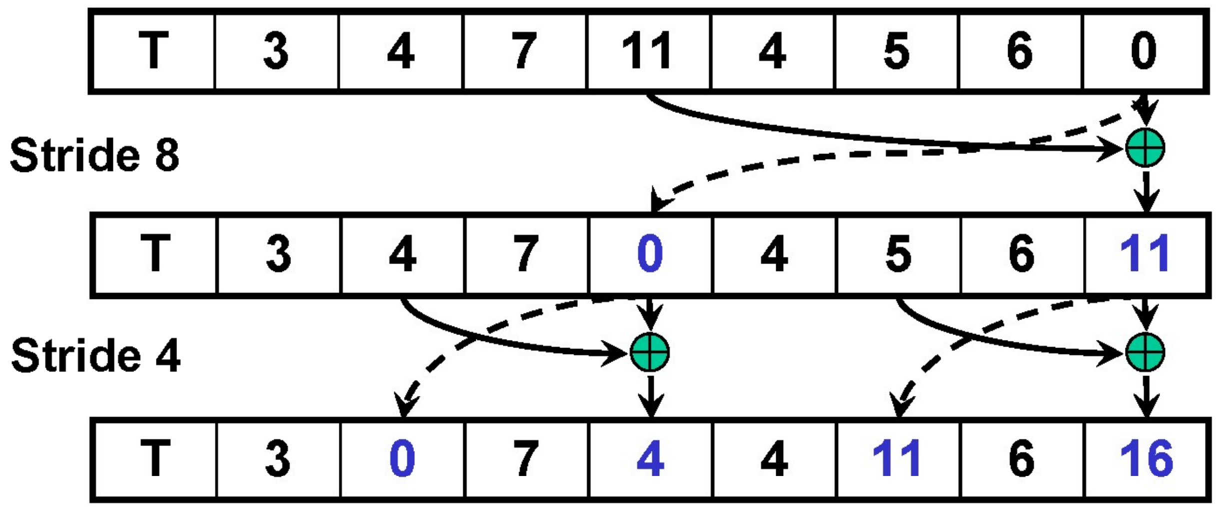
Build Scan From Partial Sums



Each ⊕ corresponds to a single thread.

Iterate log(n) times. Each thread adds value *stride* / 2 elements away to its own value. and sets the value *stride* elements away to its own *previous* value.

Build Scan From Partial Sums

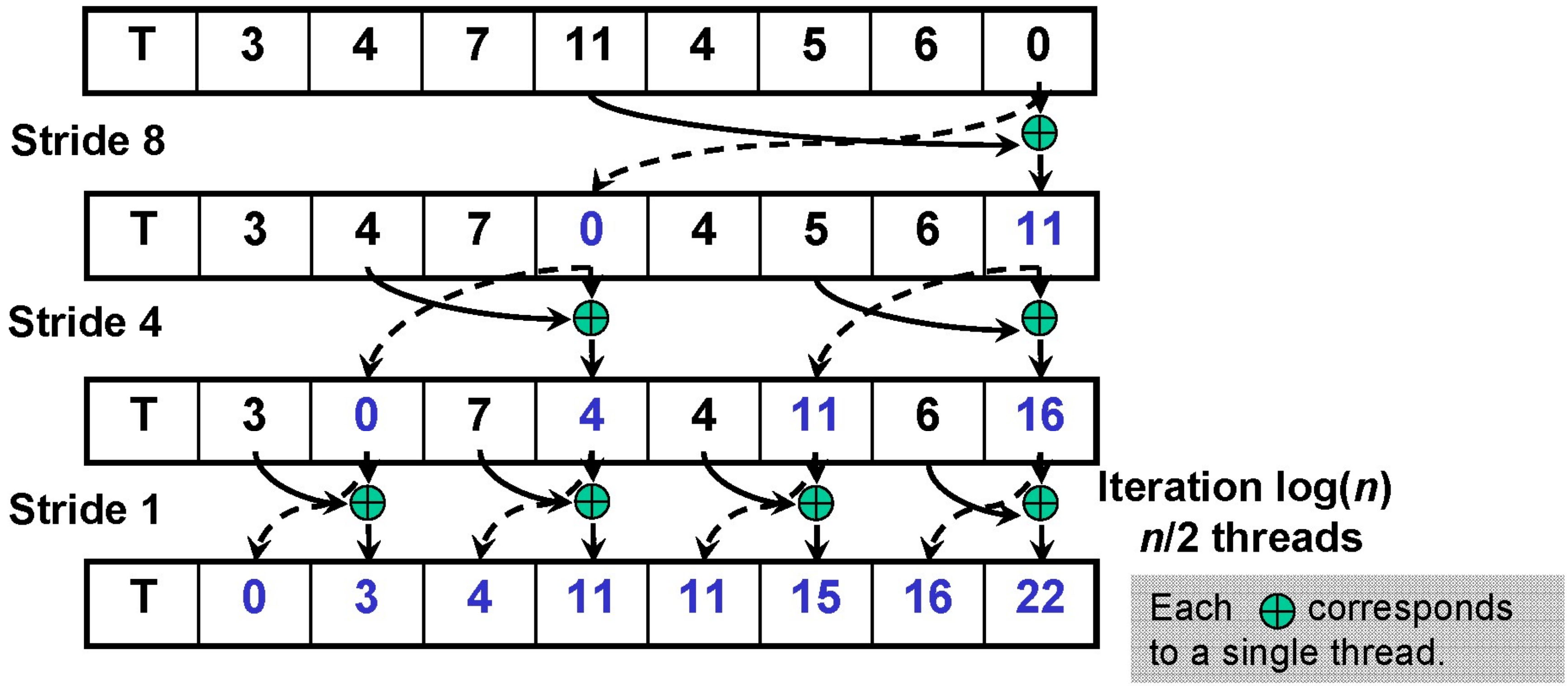


Iteration 2
2 threads

Each ⊕ corresponds to a single thread.

Iterate log(n) times. Each thread adds value *stride* / 2 elements away to its own value. and sets the value *stride* / 2 elements away to its own *previous* value.

Build Scan From Partial Sums



Done! We now have a completed scan that we can write out to device memory.

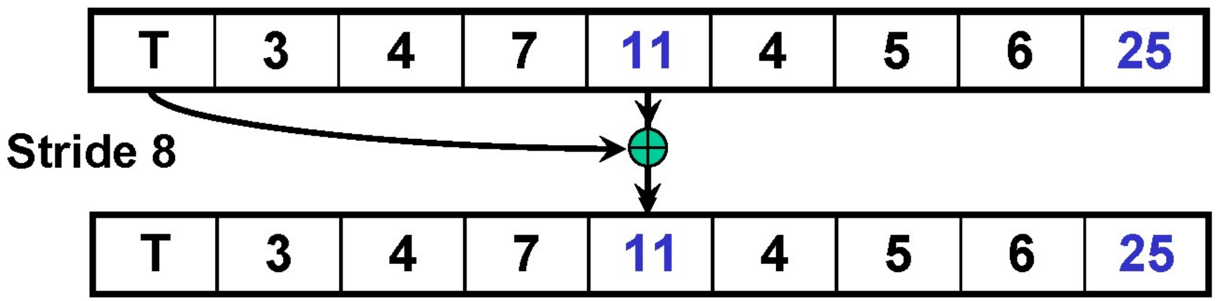
Total steps: 2 * log(n).
Total work: 2 * (n-1) adds = $O(n)$ **Work Efficient!**

Down-Sweep Variant 2: Inlusive Scan

T	3	4	7	11	4	5	6	25

We now have an array of partial sums. Let's propagate the sums back.

Build Scan From Partial Sums

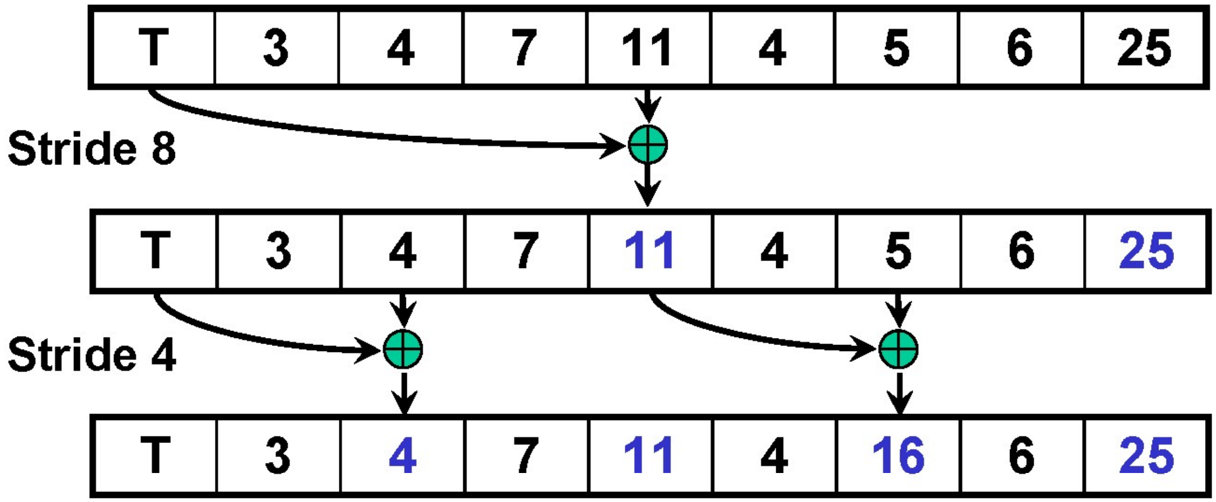


no operation

Each $\oplus$ corresponds to a single thread.

Iterate log(n) times. Each thread adds value *stride* / 2 elements away to its own value. First element adds zero.

Build Scan From Partial Sums

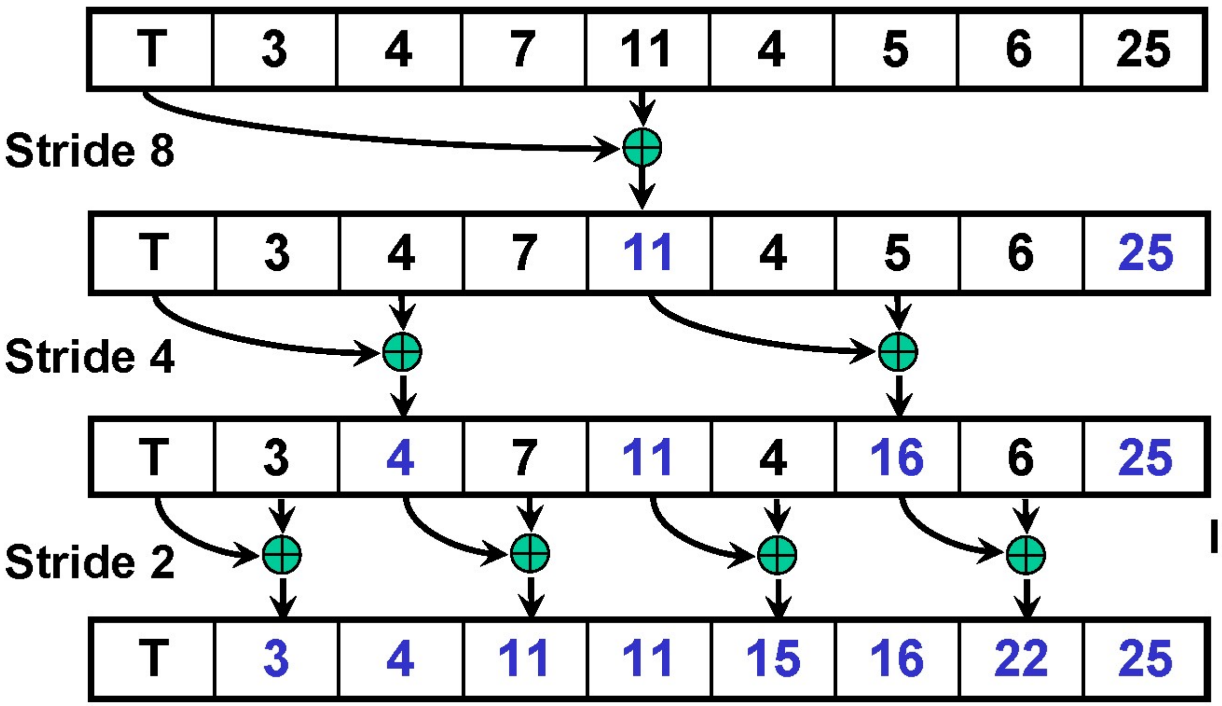


Iteration 2
2 threads

Each ⊕ corresponds to a single thread.

Iterate log(n) times. Each thread adds value *stride* / 2 elements away to its own value. First element adds zero.

Build Scan From Partial Sums



Iteration log(*n*)
***n*/2 threads**

Each ⊕ corresponds to a single thread.

Done! We now have a completed scan that we can write out to device memory.

Total steps: 2 * log(*n*).
Total work: < 2 * (*n*-1) adds = *O*(*n*) **Work Efficient!**

Summary

- **Parallel Programming requires careful planning**
  - of the branching behavior
  - of the memory access patterns
  - of the work efficiency

- **Vector Reduction**
  - branch efficient
  - bank efficient

- **Scan Algorithm**
  - based in Balanced Tree principle:
    bottom up, top down traversal

Bank Conflicts in Scan
- Non-power-of-two -

Initial Bank Conflicts on Load

- **Each thread loads two shared mem data elements**
- **Tempting to interleave the loads**

```
temp[2*thid]   = g_idata[2*thid];
temp[2*thid+1] = g_idata[2*thid+1];
```

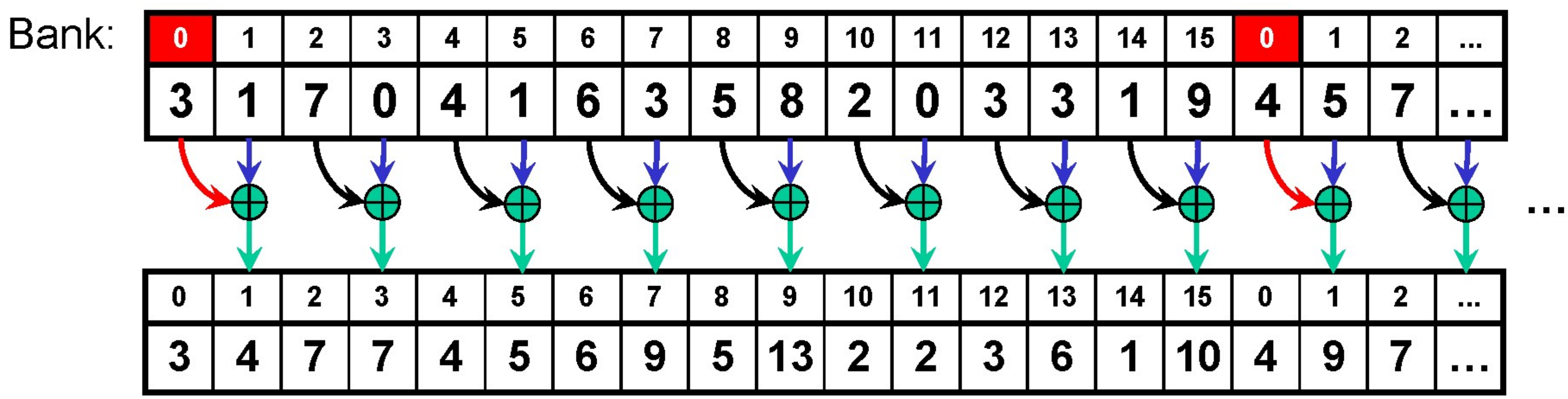
- **Threads:(0,1,2,…,8,9,10,…)→banks:(0,2,4,…,0,2,4,…)**

- **Better to load one element from each half of the array**

```
temp[thid]         = g_idata[thid];
temp[thid + (n/2)] = g_idata[thid + (n/2)];
```

Bank Conflicts in the tree algorithm

- **When we build the sums, each thread reads two shared memory locations and writes one:**
- **Th(0,8) access bank 0** with 32 banks: Th(0,16) access bank 0



First iteration: 2 threads access each of 8 banks.

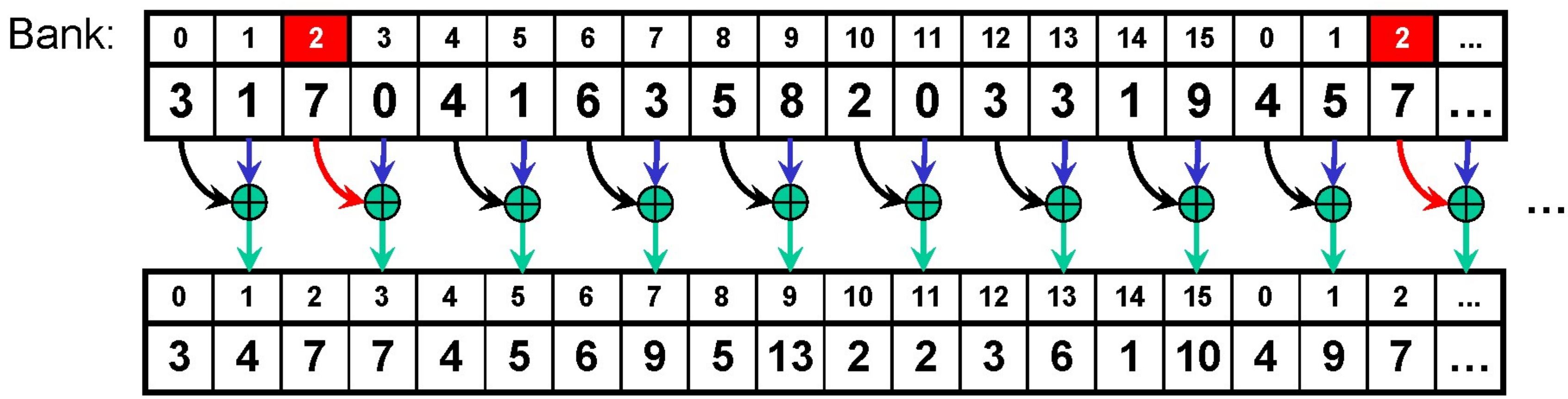
with 32 banks:
…access each of 16 banks

Each ⊕ corresponds to a single thread.

Like-colored arrows represent simultaneous memory accesses

Bank Conflicts in the tree algorithm

- **When we build the sums, each thread reads two shared memory locations and writes one:**
- **Th(1,9) access bank 2, etc.** with 32 banks: Th(1,17) access bank 2



First iteration: 2 threads access each of 8 banks. with 32 banks: …access each of 16 banks

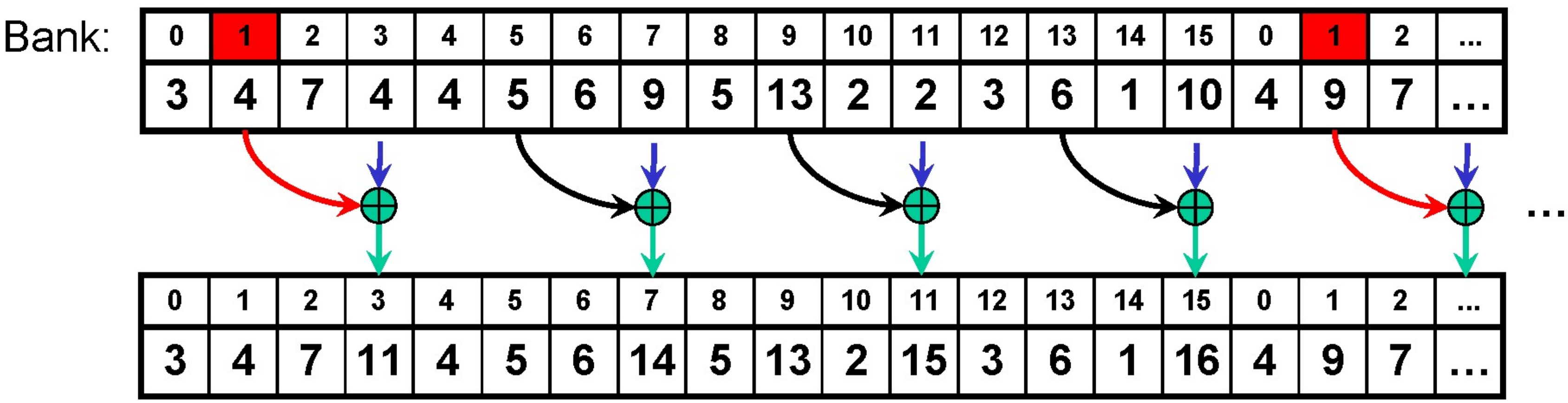
Each ⊕ corresponds to a single thread.

Like-colored arrows represent simultaneous memory accesses

Bank Conflicts in the tree algorithm

- **2nd iteration: even worse!**
  - 4-way bank conflicts; for example:
    Th(0,4,8,12) access bank 1, Th(1,5,9,13) access Bank 5, etc.

with 32 banks again same concept,
but different numbers



2nd iteration: 4 threads access each of 4 banks.

with 32 banks:
…access each of 8 banks

Each ⊕ corresponds to a single thread.

Like-colored arrows represent simultaneous memory accesses

Scan Bank Conflicts (1)

- **A full binary tree with 64 leaf nodes:**

Scale (s)	Thread addresses																															
1	0	2	4	6	8	10	12	14	16	18	20	22	24	26	28	30	32	34	36	38	40	42	44	46	48	50	52	54	56	58	60	62
2	0	4	8	12	16	20	24	28	32	36	40	44	48	52	56	60																
4	0	8	16	24	32	40	48	56																								
8	0	16	32	48																												
16	0	32																														
32	0																															
Conflicts	Banks																															
2-way	0	2	4	6	8	10	12	14	0	2	4	6	8	10	12	14	0	2	4	6	8	10	12	14	0	2	4	6	8	10	12	14
4-way	0	4	8	12	0	4	8	12	0	4	8	12	0	4	8	12																
4-way	0	8	0	8	0	8	0	8																								
4-way	0	0	0	0																												
2-way	0	0																														
None	0																															

- **Multiple 2-and 4-way bank conflicts**
- **Shared memory cost for whole tree**
  - 1 32-thread warp = 6 cycles per thread w/o conflicts
    - Counting 2 shared mem reads and one write (s[a] += s[b])
  - 6 * (2+4+4+4+2+1) = 102 cycles
  - 36 cycles if there were no bank conflicts (6 * 6)

Scan Bank Conflicts (2)

- **It's much worse with bigger trees!**
- **A full binary tree with 128 leaf nodes**
  - Only the last 6 iterations shown (root and 5 levels below)

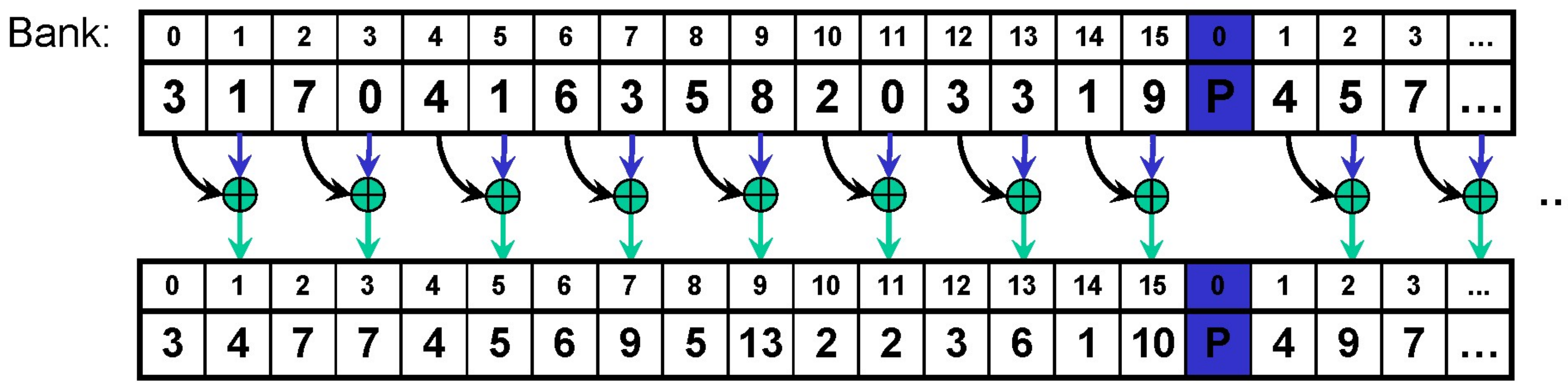
Scale (s)	Thread addresses																															
2	0	4	8	12	16	20	24	28	32	36	40	44	48	52	56	60	64	68	72	76	80	84	88	92	96	100	104	108	112	116	120	122
4	0	8	16	24	32	40	48	56	64	72	80	88	96	104	112	120																
8	0	16	32	48	64	80	96	112																								
16	0	32	64	96																												
32	0	64																														
64	0																															
Conflicts	Banks																															
4-way	0	4	8	12	0	4	8	12	0	4	8	12	0	4	8	12	0	4	8	12	0	4	8	12	0	4	8	12	0	4	8	10
8-way	0	8	0	8	0	8	0	8	0	8	0	8	0	8	0	8																
8-way	0	0	0	0	0	0	0	0																								
4-way	0	0	0	0																												
2-way	0	0																														
None	0																															

- **Cost for whole tree:**
  - 12*2 + 6*(4+8+8+4+2+1) = 186 cycles
  - 48 cycles if there were no bank conflicts! 12*1 + (6*6)

Bank Conflicts in the tree algorithm

- **We can use padding to prevent bank conflicts**
  - Just add a word of padding every 16 words:
- **No more conflicts!**

32 for full warps!



Now, within a 16-thread half-warp, all threads access different banks.

32-thread full warp!

(Note that only arrows with the same color happen simultaneously.)

Use Padding to Reduce Conflicts

- **This is a simple modification to the last exercise**

- **After you compute a shared mem address like this:**

```
Address =     stride * thid;
```

- **Add padding like this:**

```
Address += (Address >> 4); // divide by NUM_BANKS
```

>> 5 on current GPUs

- **This removes most bank conflicts**
  – Not all, in the case of deep trees

Fixing Scan Bank Conflicts

- **Insert padding every NUM_BANKS elements**

```
const int LOG_NUM_BANKS = 4; // 16 banks (32 banks on current GPUs)
int tid = threadIdx.x;          5 on current GPUs
int s = 1;
// Traversal from leaves up to root
for (d = n>>1; d > 0; d >>= 1)
{
    if (thid <= d)
    {
          int a = s*(2*tid); int b = s*(2*tid+1)
          a += (a >> LOG_NUM_BANKS); // insert pad word
          b += (b >> LOG_NUM_BANKS); // insert pad word
          shared[a] += shared[b];
    }
}
```

Fixing Scan Bank Conflicts

- **A full binary tree with 64 leaf nodes**

Leaf Nodes	Scale (s)	Thread addresses																														
64	1	0	2	4	6	8	10	12	14	17	19	21	23	25	27	29	31	34	36	38	40	42	44	46	48	51	53	55	57	59	61	63
	2	0	4	8	12	17	21	25	29	34	38	42	46	51	55	59	63															
	4	0	8	17	25	34	42	51	59																							
	8	0	17	34	51																											
	16	0	34												= Padding inserted																	
	32	0																														
	Conflicts	Banks																														
	None	0	2	4	6	8	10	12	14	1	3	5	7	9	11	13	15	2	4	6	8	10	12	14	0	3	5	7	9	11	13	15
	None	0	4	8	12	1	5	9	13	2	6	10	14	3	7	11	15															
	None	0	8	1	9	2	10	3	11																							
	None	0	1	2	3																											
	None	0	2																													
	None	0																														

- **No more bank conflicts!**
  - However, there are ~8 cycles overhead for addressing
    - For each s[a] += s[b] (8 cycles/iter. * 6 iter. = 48 extra cycles)
  - So just barely worth the overhead on a small tree
    - 84 cycles vs. 102 with conflicts vs. 36 optimal

Fixing Scan Bank Conflicts

- **A full binary tree with 128 leaf nodes**
  - Only the last 6 iterations shown (root and 5 levels below)

Scale (s)	Thread addresses																															
2	0	4	8	12	17	21	25	29	34	38	42	46	51	55	59	63	68	72	76	80	85	89	93	97	102	106	110	114	119	123	127	131
4	0	8	17	25	34	42	51	59	68	76	85	93	102	110	119	127																
8	0	17	34	51	68	85	102	119																								
16	0	34	68	102																												
32	0	68																														
64	0																															

= Padding inserted

Conflicts	Banks																															
None	0	4	8	12	1	5	9	13	2	6	10	14	3	7	11	15	4	8	12	0	5	9	13	1	6	10	14	2	7	11	15	3
None	0	8	1	9	2	10	3	11	4	12	5	13	6	14	7	15																
None	0	1	2	3	4	5	6	7																								
None	0	2	4	6																												
None	0	4																														
None	0																															

- **No more bank conflicts!**
  - Significant performance win:
    - 106 cycles vs. 186 with bank conflicts vs. 48 optimal

Fixing Scan Bank Conflicts

- **A full binary tree with 512 leaf nodes**
  - Only the last 6 iterations shown (root and 5 levels below)

Scale (s)	Thread addresses																															
8	0	17	34	51	68	85	102	119	136	153	170	187	204	221	238	255	272	289	306	323	340	357	374	391	408	425	442	459	476	493	510	527
16	0	34	68	102	136	170	204	238	272	306	340	374	408	442	476	510																
32	0	68	136	204	272	340	408	476																								
64	0	136	272	408																												
128	0	272																														
256	0																															

= Padding inserted

Conflicts	Banks																															
None	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
2-way	0	2	4	6	8	10	12	14	0	2	4	6	8	10	12	14																
2-way	0	4	8	12	0	4	8	12																								
2-way	0	8	0	8																												
2-way	0	0																														
None	0																															

- **Wait, we still have bank conflicts**
  - Method is not foolproof, but still much improved
  - 304 cycles vs. 570 with bank conflicts vs. 120 optimal
- **But it does not pay off to optimize for the rest. Address calculations are getting too expensive**

Summary

- **Parallel Programming requires careful planning**
  - of the branching behavior
  - of the memory access patterns
  - of the work efficiency

- **Vector Reduction**
  - branch efficient
  - bank efficient

- **Scan Algorithm**
  - based in Balanced Tree principle:
    bottom up, top down traversal

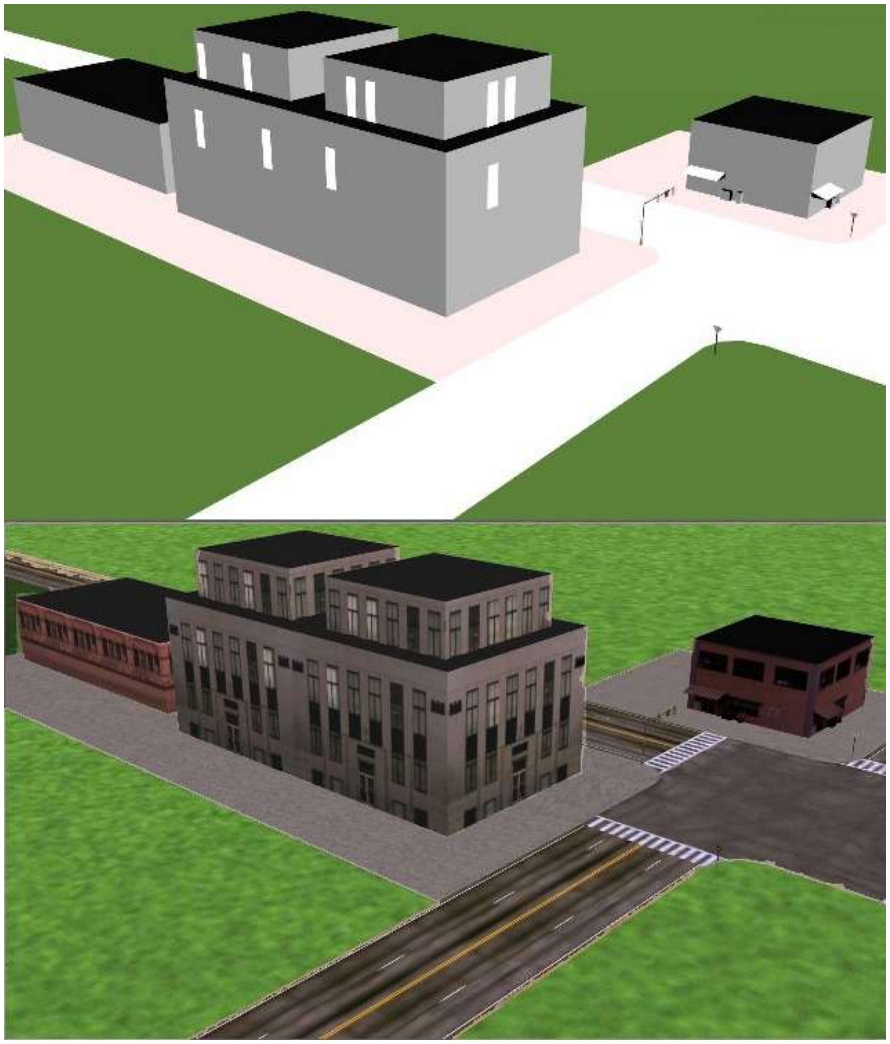
GPU Texturing

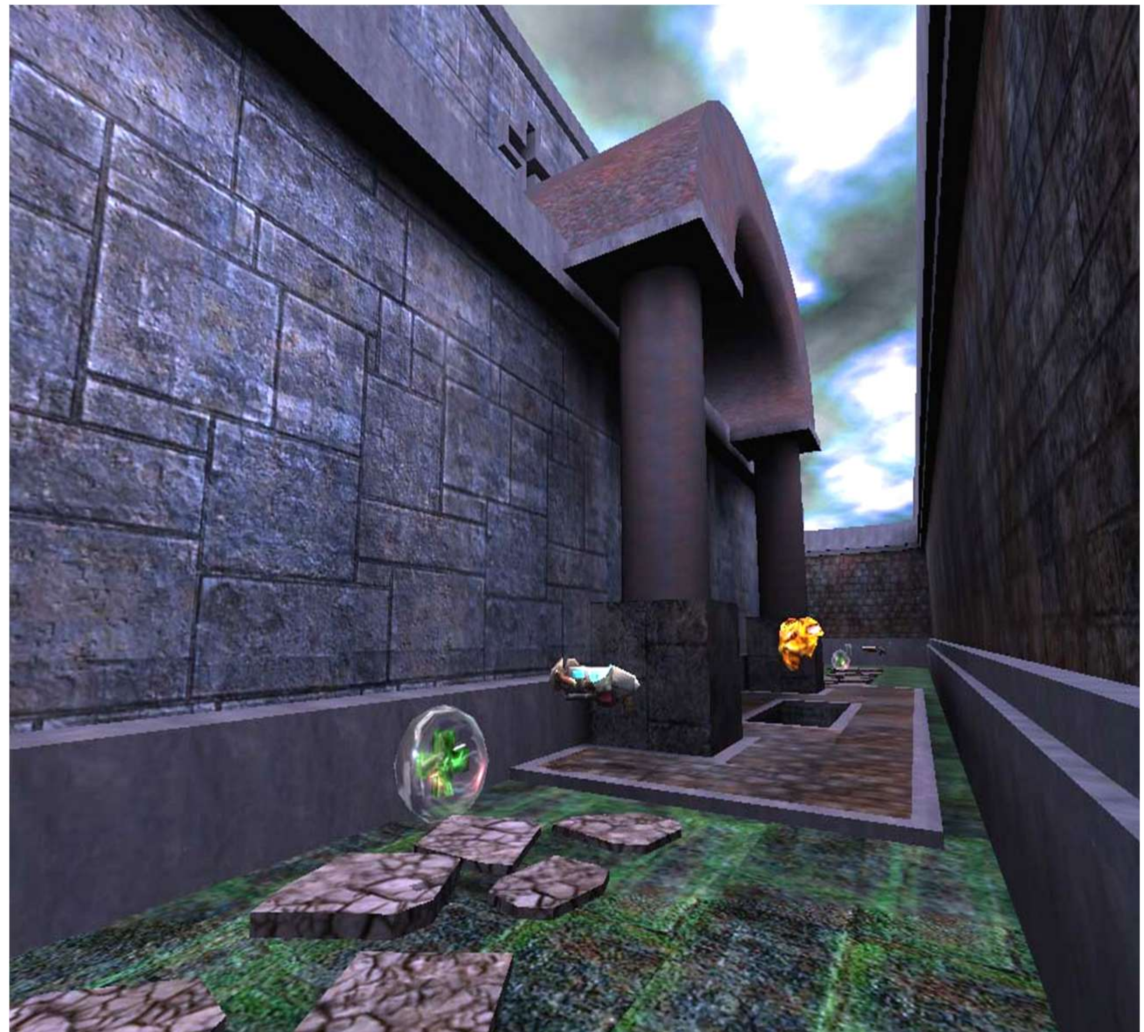
GPU Texturing

Rage / id Tech 5 (id Software)

Why Texturing?

- Idea: enhance visual appearance of surfaces by applying fine / high-resolution details





OpenGL Texture Mapping

- Basis for most real-time rendering effects
- Look and feel of a surface
- Definition:
  - A *regularly sampled function* that is mapped onto every *fragment* of a surface
  - Traditionally an image, but…
- Can hold arbitrary information
  - Textures become general data structures
  - Sampled and interpreted by fragment programs
  - Can render into textures → important!

Types of Textures

- Spatial layout
  - Cartesian grids: 1D, 2D, 3D, 2D_ARRAY, …
  - Cube maps, …

for Vulkan, see `vkImageView`

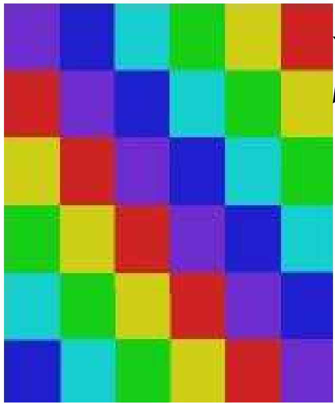
- Formats (too many), e.g. OpenGL
  - GL_LUMINANCE16_ALPHA16
  - GL_RGB8, GL_RGBA8, …: integer texture formats
  - GL_RGB16F, GL_RGBA32F, …: float texture formats
  - compressed formats, high dynamic range formats, …

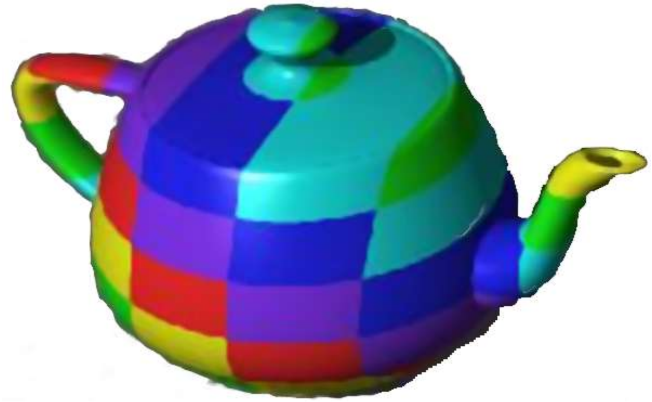
- External (CPU) format vs. internal (GPU) format
  - OpenGL driver converts from external to internal

for Vulkan, see vkImage
and `vkImageView`

use `VK_IMAGE_TILING_OPTIMAL`
for `VkImageCreateInfo::tiling`

Texturing: General Approach

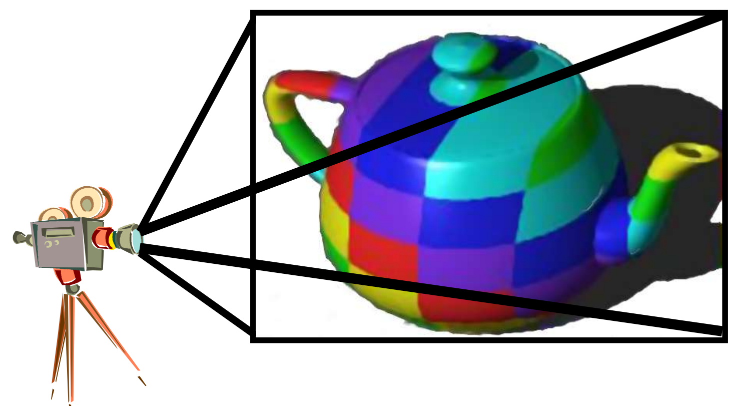




Texture space *(u,v)* **Object space** (x_O,y_O,z_O) **Image Space** (x_I,y_I)

Parametrization

Rendering (Projection etc.)



Texture Mapping

2D (3D) Texture Space

Texture Transformation

2D Object Parameters

Parameterization

3D Object Space

Model Transformation

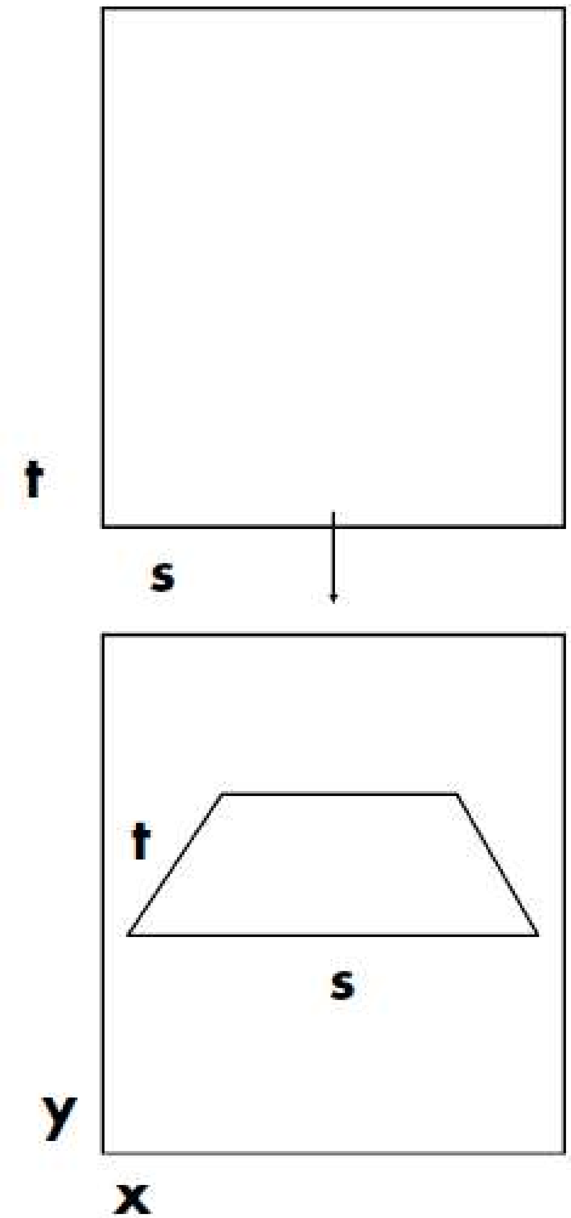
3D World Space

Viewing Transformation

3D Camera Space

Projection

2D Image Space



Kurt Akeley, Pat Hanrahan

Thank you.