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GPU Kernels with Thread Cooperation

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Going Parallel : Thread Cooperation

Motivation: Limits of Trivial Parallelization

Reductions : e.g. dot product

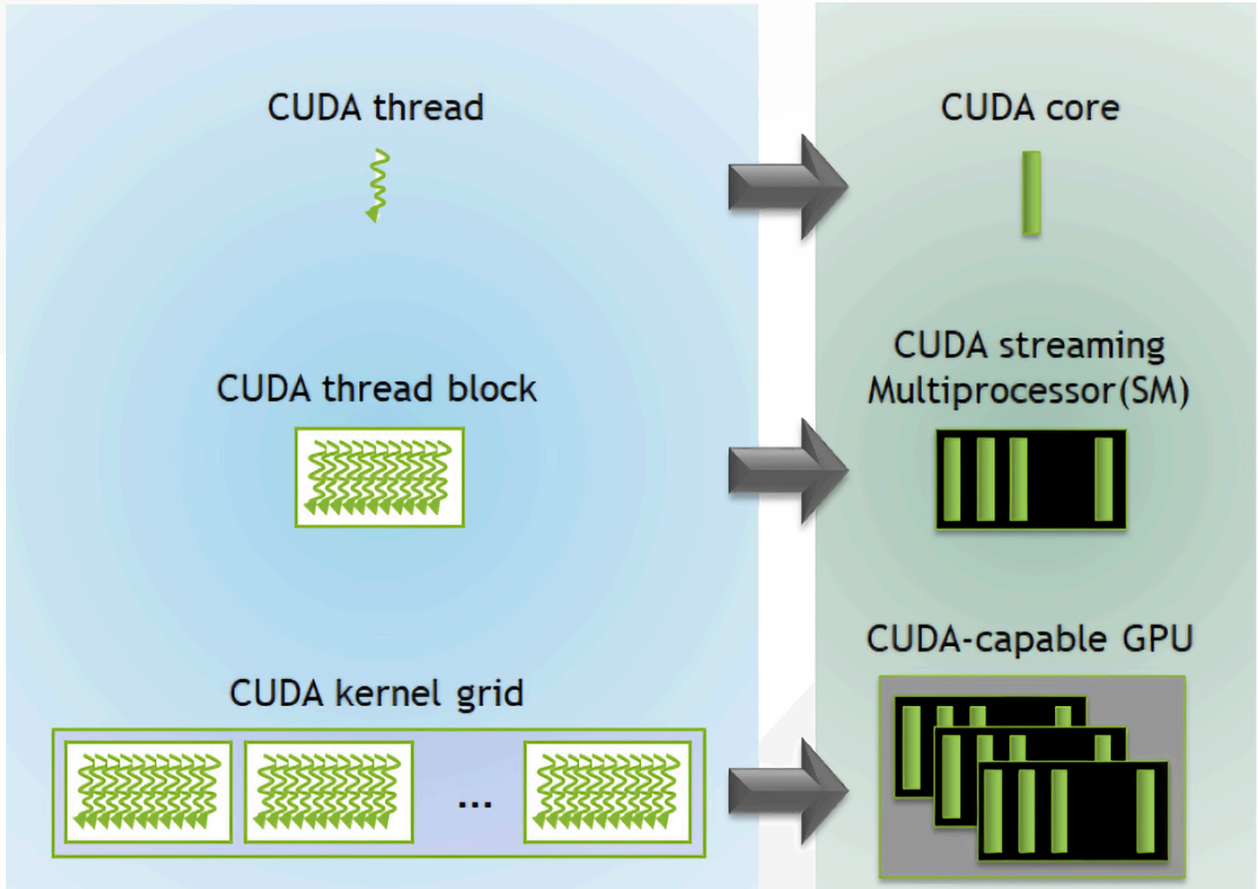
```
int dot(int *x, int *y, int n) {
    int sum = 0;
    for(auto i=0; i<n; ++i) {
        sum += x[i]*y[i];
    }
    return sum;
}
```

Scan : e.g. prefix sum

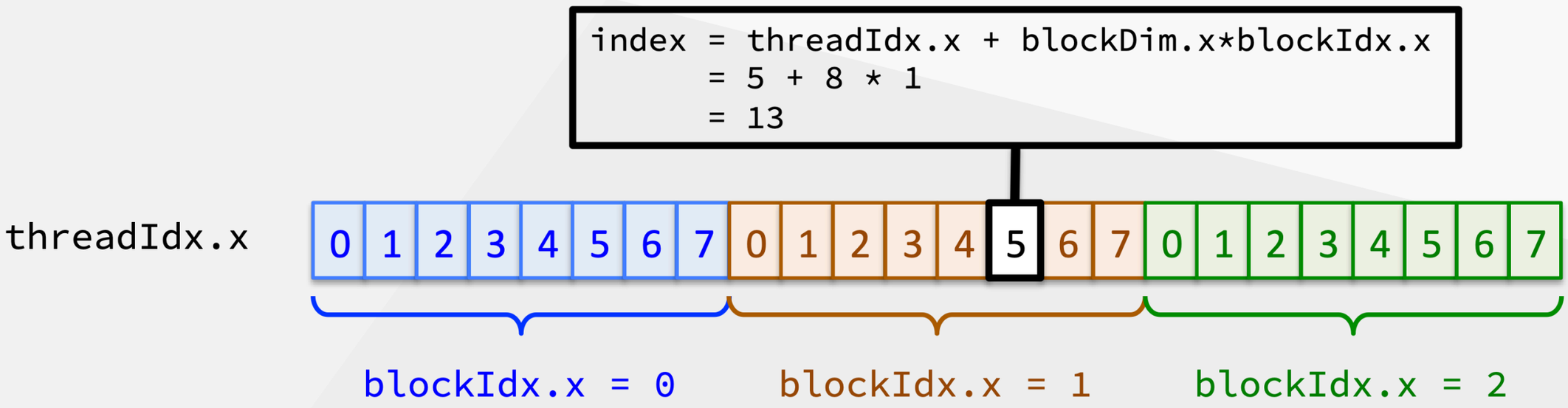
```
void prefix_sum(int *x, int n) {
    for(auto i=1; i<n; ++i) {
        x[i] += x[i-1];
    }
}
```

Pipelined Loops : e.g. apply blur kernel twice

```
void twice_blur(float *in, float *out, int n) {
    float buff[n];
    for(auto i=1; i<n-1; ++i) {
        buff[i] = 0.25*(in[i-1]+in[i+1]+2.0*in[i]);
    }
    for(auto i=2; i<n-2; ++i) {
        out[i] = 0.25*(buff[i-1]+buff[i+1]+2.0*buff[i]);
    }
}
```




```
auto index = threadIdx.x + blockIdx.x*blockDim.x
```



Types of Cooperation

- **Cooperation between Threads within the SAME Block**
  - All threads in a block run on the same SMX
  - Shared resources such as L1 cache and shared memory
  - CUDA provides mechanisms for synchronization at the block level and lower
  - No necessary synchronization between threads in different blocks

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  - No necessary synchronization between threads in different blocks
- **Cooperation between DIFFERENT Blocks**
  - Cooperation must occur through global memory
  - CUDA supports *atomic operations*
  - (On Grace Hopper (GH) shared memory of other SMX are addressable to some extent)

Block Level Cooperation

Cooperating through shared memory:

- Shared memory is simply a user-managed cache
- Threads in a block can see the same shared memory
- Shared memory is not visible to threads in other blocks executing on the same SMX

Block Level Cooperation

Cooperating through shared memory:

- Shared memory is simply a user-managed cache
- Threads in a block can see the same shared memory
- Shared memory is not visible to threads in other blocks executing on the same SMX
- Shared memory is a limited resource (**64 KB/SM on a legacy card P100**):
  - Shared memory usage per block limits how many blocks can run simultaneously on an SMX
  - One thread block can allocate 64 KB for itself. . .
  - . . . two thread blocks can allocate 32 KB each

Shared Memory

- What changes with different GPU architectures:
  - P100: L1 cache and shared mem. have **fixed** sizes
  - A100 & V100: L1 cache and shared mem. are now unified and their portion is **configurable**
  - 64KB/SM on a P100 and up to 128KB/SM on an A100
  - Up to 228KB/SM on a Grace-Hopper (GH)

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  - 64KB/SM on a P100 and up to 128KB/SM on an A100
  - Up to 228KB/SM on a Grace-Hopper (GH)
- What does NOT change from P100 upwards:
  - Shared memory is divided in 32 equal memory banks, where
  - 32-bit words map to successive banks
  - Each memory bank has a bandwidth of 32 bits/cycle
  - When more than one thread writes to the same bank the write operations are serialized (**bank conflicts**)

Moving Data To and From Shared Memory

- P100, V100, A100, and GH **coalesce global memory access** into 32 byte transactions:
  - For example, a block with 32 threads reading 1 `float` per thread requires only 4 global memory transactions (if and only if the `float`s are consecutive in global memory)
  - Each of these `float`s gets placed into **consecutive shared memory banks** without any bank conflicts

Moving Data To and From Shared Memory

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  - Each of these `float`s gets placed into **consecutive shared memory banks** without any bank conflicts
- Things to watch out for:
  - When reading strided data, part of that 32 byte memory transaction will go unused
  - This will decrease the effective memory bandwidth

Copy Kernel with Shared Memory

- Do we need shared memory for this? Nope.
- This kernel is launched as usual.
- What if `DECIMATE > 1` ?
- Have we got any memory bank conflicts?

A Naive Downsampling Kernel

```
template <int BSIZE, int DECIMATE=1>
__global__ void downsample(const float* in, float* out, int n) {
    // Allocate shared memory statically
    __shared__ float buffer[BSIZE];
    auto idx = threadIdx.x + blockIdx.x * BSIZE;
    // Coalesced reads - no bank conflicts
    if (idx * DECIMATE < n)
        buffer[threadIdx.x] = in[idx * DECIMATE];
    // Ensure all threads finish reading
    __syncthreads();
    // Coalesced writes
    if (idx < n/DECIMATE)
        out[idx] = buffer[threadIdx.x]; }
```

Synchronizing Threads

What does `__syncthreads()` do?

- All threads in the block wait for each other to finish loading data into shared memory
- Only after `__syncthreads()` the memory read by other threads is guaranteed to be visible to all other threads in the block
- Do we need synchronization in this example? There's no thread cooperation, so ... nope!
- What might happen if we place the sync inside the if statement?

1D Blur Kernel

A simple stencil operation:

$$\mathrm{out}_i = 0.25 \times (\mathrm{in}_{i-1} + 2.0 \times \mathrm{in}_i + \mathrm{in}_{i+1})$$

- Each output value is a linear combination of neighbors in input array

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CPU Implementation

```
void blur(double *in, double *out, int n) {
    float buff[n];
    for(auto i=1; i<n-1; ++i) {
        out[i] = 0.25*(in[i-1] + 2.0*in[i] + in[i+1]);
    }
}
```

1D Blur Kernel

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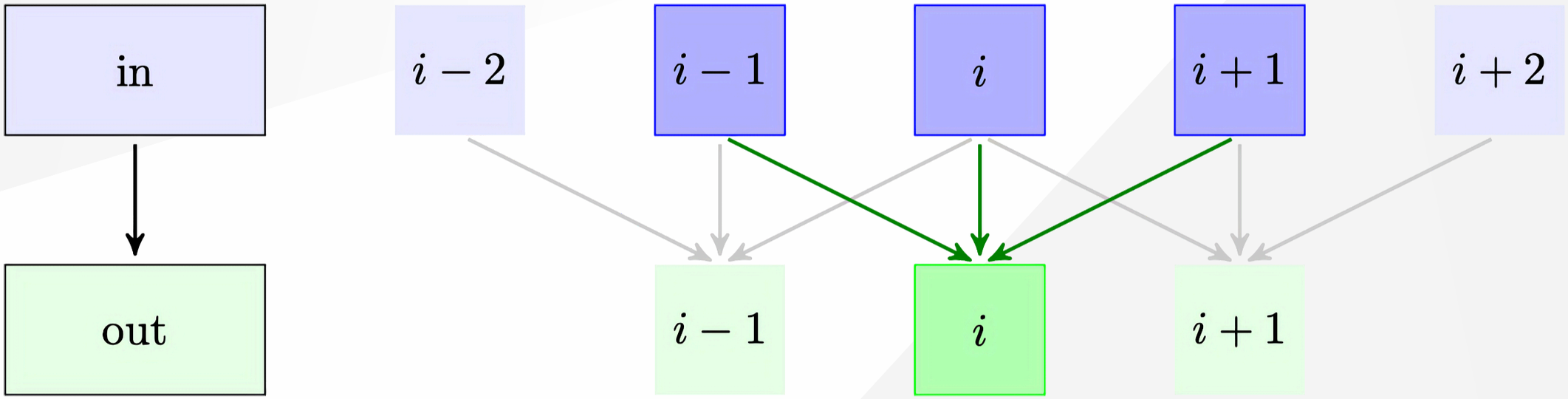
- Each output value is a linear combination of neighbors in input array

GPU Implementation

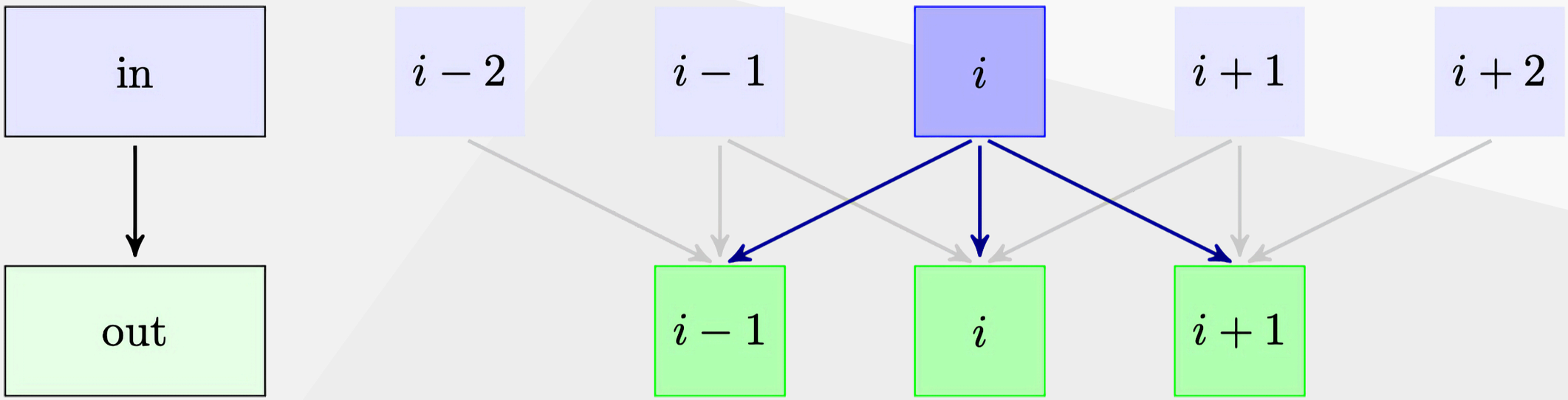
```
__global__
void blur(const double* in, double* out, int n) {
    int i = threadIdx.x + 1; // assume one thread block
    if(i<n-1) {
        out[i] = 0.25*(in[i-1] + 2.0*in[i] + in[i+1]);
    }
}
```

Our first CUDA implementation of the blur kernel has each thread load the three values required to form its output

Each thread has to load 3 values from global (?) memory to calculate its output

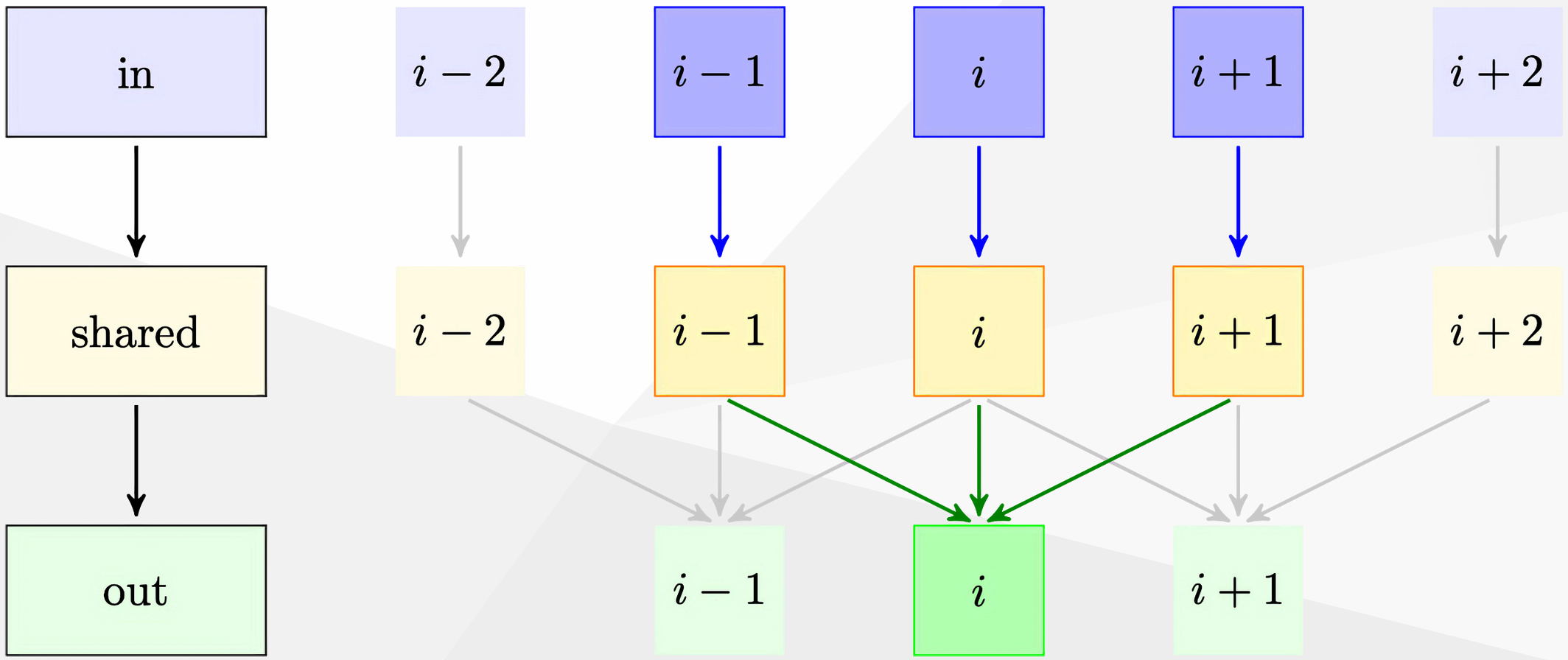


Alternatively, each value in the input array has to be added 3 times into the output array (why is this far worse than the above approach?)



To take advantage of shared memory the kernel is split into two stages:

1. Load `in[i]` into shared memory `buffer[i]`
   - One thread has to load `in[0]` & `in[n-1]`
2. Use values `buffer[i-1:i+1]` to compute kernel



Blur Kernel with Shared Memory - Single Block

```
template <int BSIZE >
__global__
void blur_shared_block(const double* in, double* out, int n) {
    __shared__ double buffer[BSIZE];
    auto i = threadIdx.x + 1;

    if(i<n-1) {
        // load shared memory
        buffer[i] = in[i];
        // use one thread to handle the boundary conditions
        if(i==1) {
            buffer [0] = in [0];
            buffer[n-1] = in[n-1];
        }
        __syncthreads();
        out[i] = 0.25*(buffer[i-1] + 2.0*buffer[i] + buffer[i+1]);
    }
}
```

- Do we need synchronization in this example? Yes!
- Thread `i` needs to wait for threads `i-1` and `i+1` to load values into `buffer`

Declaring Shared Memory: Two Ways

Static Allocation

When the amount of memory is known at compile time:

```
__shared__ double buffer[128];
```

- Here there are 128 double-precision values (1024 bytes) of memory shared by all threads.

Declaring Shared Memory: Two Ways

Static Allocation

When the amount of memory is known at compile time:

```
__shared__ double buffer[128];
```

- Here there are 128 double-precision values (1024 bytes) of memory shared by all threads.

Dynamic Allocation

When the memory is determined at run time:

```
extern __shared__ double buffer[];
```

- Note the `extern` keyword.
- The size of memory to be allocated is specified when the kernel is launched

Launch Kernels with Static Shared Memory

- Always need to allocate enough shared memory for the given block size.
- Our `blur_shared_block` kernel needed 2 extra elements (`num_threads + 2`)

Launching our `blur_shared_block` Kernel

```
// Setting the block size to 128 threads
auto n = 128;
blur_shared_block <128+2><<<num_blocks , n>>>(x0, x1, n);
```

Launch Kernels with Dynamic Shared Memory

An additional parameter is added to the launch syntax

```
blur_shared<<<grid_dim, block_dim, shared_size>>>(...);
```

- `shared_size` is the shared memory **in bytes** to be dynamically allocated **per thread block**

```
__global__
void blur_shared(double *in, double* out, int n) {
    extern __shared__ double buffer [];
    int i = threadIdx.x + 1;
    // ...
}

// in main ()
auto block_dim = n;
auto size_in_bytes = (n+2)*sizeof(double);

blur_shared<<<1, block_dim, size_in_bytes>>>(x0, x1, n);
```

Optimizing Shared Memory Use

It is possible to allocate multiple variables as shared memory.

- If the shared memory is used separately, you can use a union to “overlap” the storage
- Shared memory is a limited resource

separate storage

```
__global__
void kernel1() {
  // 1536 bytes
  __shared__ int X[128];
  __shared__ double Y[128];

  // OK
  X[i] = (int)Y[i];
}
```

overlapping storage

```
__global__
void kernel2(int n) {
  // 1024 bytes
  __shared__ union {
    int X[128];
    double Y[128];
  } buf;

  // not OK
  buf.X[i] = (int)buf.Y[i];
}
```

Finding Resource Usage of Kernels

The nvcc flag `--resource-usage` will print the resources used by each kernel during compilation:

- shared memory
- constant memory
- registers

```
> nvcc --resource-usage -arch=sm_60 shared.cu
ptxas info  : 0 bytes gmem
ptxas info  : Compiling entry function '_Z7kernel2i' for
ptxas info  : Function properties for _Z7kernel2i
0 bytes stack frame, 0 bytes spill stores, 0 bytes spill loads
ptxas info  : Used 6 registers, 1024 bytes smem, 324 bytes cmem[0]
ptxas info  : Compiling entry function '_Z7kernel1v' for
ptxas info  : Function properties for _Z7kernel1v
0 bytes stack frame, 0 bytes spill stores, 0 bytes spill loads
ptxas info  : Used 6 registers, 1536 bytes smem, 320 bytes cmem[0]
> c++filt _Z7kernel2i
kernel2(int)
```

Note: the kernel names have been mangled

Back to our Blur Kernel

A version of the blur kernel for arbitrarily large `n` is provided in `blur.cu` in the example code. One relevant thing to note is:

- the `in` and `out` arrays use global indexes. . .
- . . . and the shared memory uses thread block local indexes

have a go at the code!
What's the speedup when using shared memory?
extra: Modify the `blur_shared` kernel to allocate shared memory dynamically.

Blur Kernel Results

and all this for ... no speedup at all?
This kernel operates on consecutive memory.
Coalesced reads and writes.
Turns out that L1 cache does a pretty good job!
You might get some speedup if you try this out in a very old GPU. • GPUs prior to P100 do not cache on L1 by default.

Fusing Kernels

- Sometimes a workflow uses the output of one kernel as the input of another.
  - On the CPU these can be optimized by keeping the intermediate result in cache for the second kernel
  - On the GPU one can fuse the two operations into the same kernel and use shared memory
- An example: two concatenated stencil operations

Naive Double-Blur

```
// Setting the block size to 128 threads
auto n = 128;
blur_shared_block<128+2><<<num_blocks, n>>>(x0, x1, n);
blur_shared_block<128+2><<<num_blocks, n>>>(x1, x2, n);
```

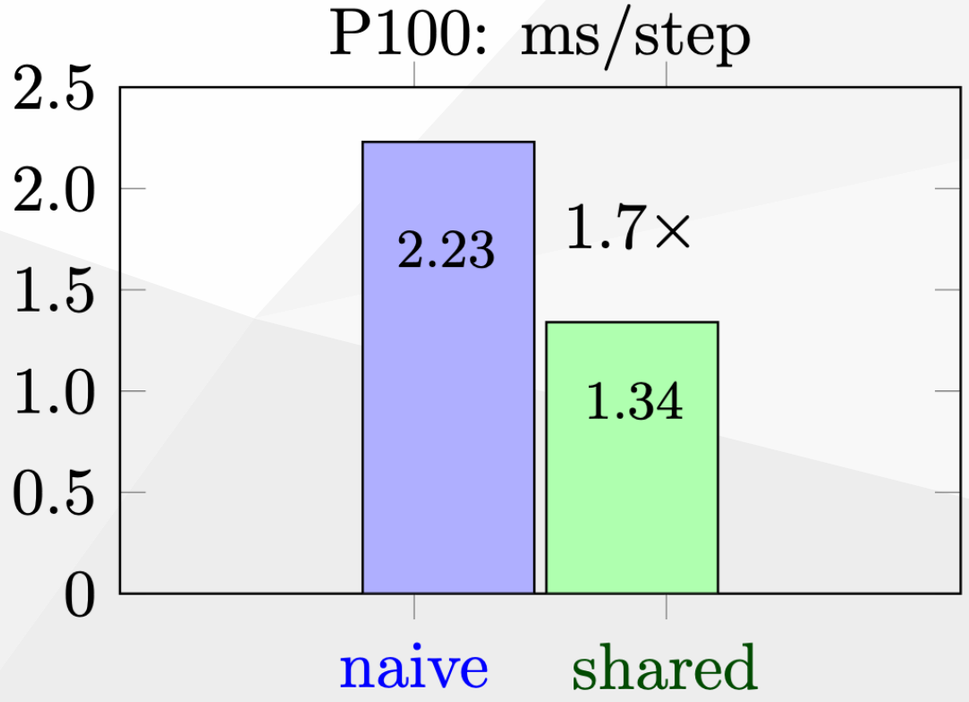
- **Fusing** these two operations will save us a round trip to global memory!

Double-Blur: CUDA with Shared Memory

```
__global__
void blur_twice(const double* in, double* out, int n) {
    extern __shared__ double buffer[];

    auto block_start = blockDim.x * blockIdx.x;
    auto block_end   = block_start + blockDim.x;
    auto lid = threadIdx.x + 2;
    auto gid = lid + block_start;

    auto blur = [] (int pos, const double* field) {
        return 0.25*(field[pos-1] + 2.0*field[pos] + field[pos+1]);
    };

    if(gid<n-2) {
        buffer[lid] = blur(gid, in);
        if(threadIdx.x==0) {
            buffer[1]            = blur(block_start+1, in);
            buffer[blockDim.x+2] = blur(block_end+2, in);
        }
    }

    __syncthreads();

    if(gid<n-2) {
        out[gid] = blur(lid, buffer);
    }
}
```

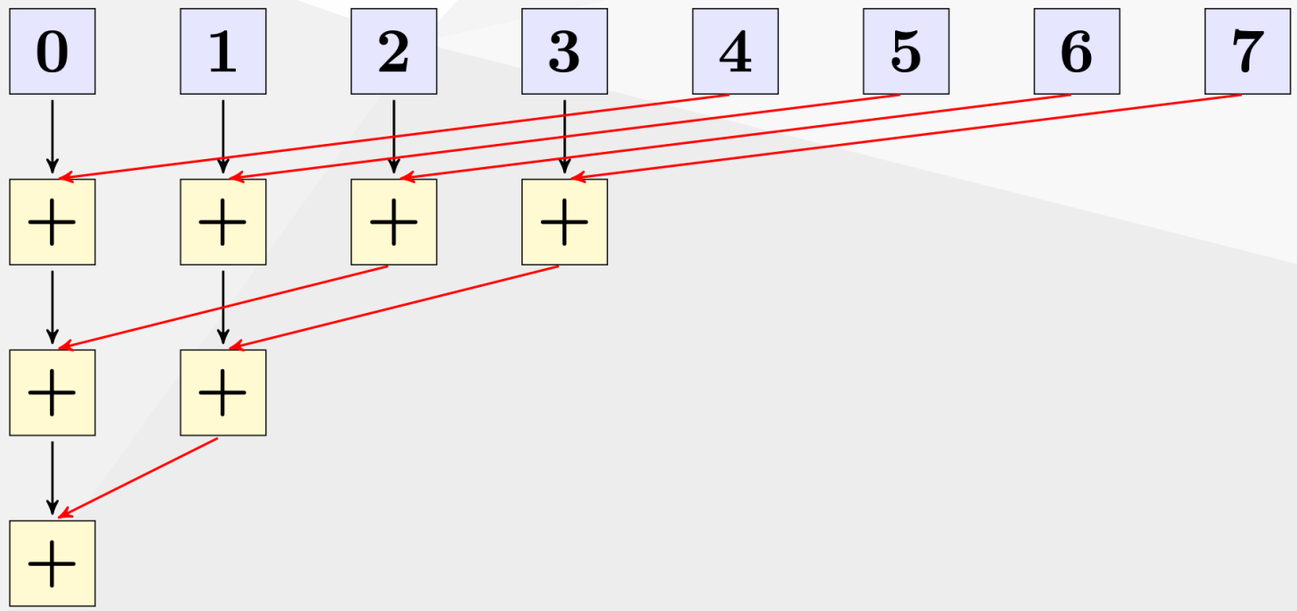
Dissecting the Speedup

- These types of kernels do very little math per loaded `double` from global memory
- Total runtime heavily dominated by the global memory bandwidth
  - Global memory BW: 500GB/s (P100), 1320GB/s (A100)
  - Shared memory BW: 8850GB/s (P100), 18140GB/s (A100)



Exercise: Shared Memory

- Finish the `shared/string_reverse.cu` example. Assume $n \leq 1024$.
  - With or without shared memory
  - **extra**: without any synchronization
- Implement a dot product in CUDA in `shared/dot.cu`
  - The host version has been implemented as dot_host()
  - Assume $n \leq 1024$
  - **extra**: how would you extend it to work for arbitrary $n > 1024$ and n threads?



Back to Cooperation

Cooperation in a GPU code can occur at multiple levels:

- **Intra-block** cooperation:
  - Between threads in a warp;
  - Between threads in thread block;
- **Inter-block** cooperation:
  - Between threads in grid;
  - Between threads in different kernels

Synchronization might be required if more than one thread wants to modify (write) one of these shared resources.

Race Conditions

> A race condition can occur when more than one thread attempts to access the same memory location concurrently and at least one access is a write.

```
__global__
void race(int* x) {
  ++x[0]
}

int main(void) {
  int* x = malloc_managed<int>(1);
  race<<<1, 2>>>(x);
  cudaDeviceSynchronize();
  // what value is in x[0]?
}
```

No Race

t0	t1	x
R		0
I		0
W		1
	R	1
	I	1
	W	2

Race

t0	t1	x
R		0
	R	0
I		0
W		1
	I	1
	W	1

Example where two threads `t0` and `t1` both increment x in memory. The threads use: read (R); write (W); and increment (I).

- Race conditions produce strange and unpredictable results
- Synchronization is required to avoid race conditions

Synchronization Within a Block

Threads in the **same thread block** can use `__syncthreads()` to synchronize on access to shared memory and global memory

```
__global__
void update(int* x, int* y) {
  int i = threadIdx.x;
  if (i == 0) x[0] = 1;
  __syncthreads();
  if (i == 1) y[0] = x[0];
}

int main(void) {
  int* x = malloc_managed<int>(1);
  int* y = malloc_managed<int>(1);
  update<<<1,2>>>(x, y);
  cudaDeviceSynchronize();
  // both x[0] and y[0] equal 1
}
```

Note: All threads in a block must reach the `__syncthreads()` otherwise strange things (may) happen!

Atomic Operations

What is the output of the following code?

```
__global__ void count_zeros(int* x, int* count) {
  int i = threadIdx.x;
  if (x[i]==0) *count+=1;
}

int main(void) {
  int* x = malloc_managed<int>(1024);
  int* count = malloc_managed<int>(1);
  count = 0;
  for (int i=0; i<1024; ++i) x[i]=i%128;

  count_zeros<<<1, 1024>>>(x, count);
  cudaDeviceSynchronize();
  printf("result %d\n", *x); // expect 8
  cudaFree(x);
  return 0;
}
```

Atomic Operations

An **atomic memory operation** is an uninterruptable read-modify-write memory operation:

- Serializes contentious updates from multiple threads;
- **The order** in which concurrent atomic updates are performed **is not defined**;
- However none of the atomic updates will be lost

race

```
__global__ void inc(int* x) {
  *x += 1;
}
```

no race

```
__global__ void inc(int* x) {
  atomicAdd(x, 1);
}
```

Atomic Add

```
// pseudo-code implementation of atomicAdd
__device__ int atomicAdd(int *p, int v) {
  int old;
  exclusive_single_thread {
    old = *p; // Load from memory
    *p = old + v; // Store after adding v
  }
  return old; // return original value before modification
}
```

Atomic Functions

CUDA has a range of atomic functions, including:

- **Arithmetic**: `atomicAdd()`, `atomicSub()`, `atomicMax()`, `atomicMin()`, `atomicCAS()`, `atomicExch()`
- **Logical**: `atomicAnd()`, `atomicOr()`, `atomicXor()`

These functions take both 32 and 64 bit arguments

- `atomicAdd()` gained supported for double in CUDA 8 with Pascal.
- see the CUDA Programming Guide for specific details.

Things to consider

- Atomics are slower than normal accesses:
  - Performance can degrade when many threads attempt atomic operations on few memory locations
- Try to avoid or minimize the number of atomic operations:
  - Attempt to use shared memory and structure algorithms to avoid synchronization wherever possible.
  - Try performing operation at warp level or block level
  - Use atomics for infrequent, sparse and/or unpredictable global communication
- Further reading:
  - CUDA weakly-ordered memory model
  - Memory fence functions

Exercises: Atomics

- What is `shared/hist.cu` supposed to do?
  - What is the output?
  - Fix it to get the expected output
- Improve `shared/dot.cu` to work for arbitrary n