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CUDA: Cooperation Between Threads

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Cooperating Threads

Most algorithms do not lend themselves to trivial parallelization

reductions : e.g. dot product

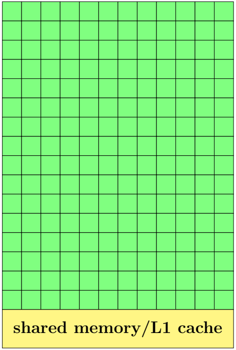
```
int dot(int *x, int *y, int n){
  int sum = 0.;
  for(auto i=0; i<n; ++i)
    sum += x[i]*y[i];
  return sum;
}
```

scan : e.g. prefix sum

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

fusing pipelined stencil 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] = 0.25f*(in[i-1]+in[i+1]+2f*in[i]);
  for(auto i=2; i<n-2; ++i)
    out[i] = 0.25f*(buff[i-1]+buff[i+1]+2f*buff[i]);
}
```



Block-Level synchronization

CUDA provides mechanisms for **cooperation between threads in a thread block**.

- All threads in a block run on the same SMX
- Resources for synchronization are at SMX level
- No synchronization between threads in different blocks

Cooperation between threads requires sharing of data

- all threads in a block can share data using **shared memory**
- shared memory is **not visible** to threads in other thread blocks
- all threads in a block are on the same SMX
- no synchronization possible between threads in different thread blocks
  - ... except via atomic operations on global memory

One-dimensional blur kernel

$$\text{out}_i \leftarrow 0.25 \times (\text{in}_{i-1} + 2 \times \text{in}_i + \text{in}_{i+1})$$

- each output value is a linear combination of neighbours in input array
- first we look at naiive implementation

Host implementation of blur kernel

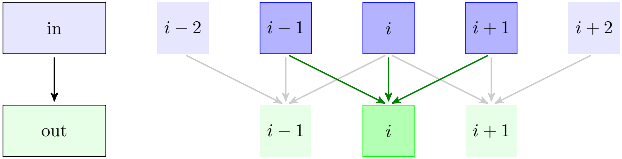
```
void blur(double *in, double *out, int n){
  float buff[n];
  for(auto i=1; i<n-1; ++i)
    out[i] = 0.25*(in[i-1] + 2*in[i] + in[i+1]);
}
```

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

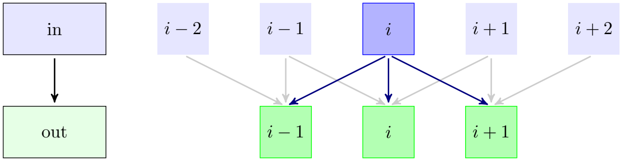
First implementation of blur kernel

```
__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*in[i] + in[i+1]);
  }
}
```

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

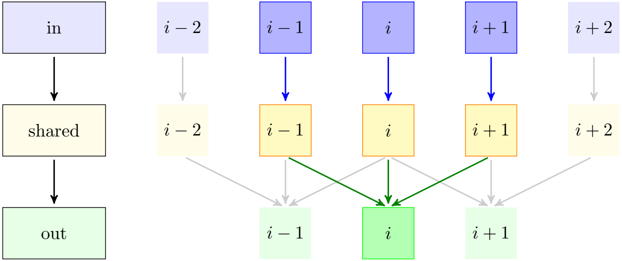


Alternatively, each value in the input array has to be loaded 3 times



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]`
2. use values `buffer[i-1:i+1]` to compute kernel



Blur kernel with shared memory

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

    auto i = threadIdx.x + 1;

    if(i<n-1) {
        // load shared memory
        buffer[i] = in[i];
        if(i==1) {
            buffer[0] = in[0];
            buffer[n] = in[n];
        }

        __syncthreads();

        out[i] = 0.25*(buffer[i-1] + 2.0*buffer[i] + buffer[i+1]);
    }
}
```

Declaring shared memory

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

- the size of memory to be allocated is specified when the kernel is launched

Synchronizing threads

```
__syncthreads();
```

- threads wait for all threads in thread block to finish loading shared memory buffer
- thread i needs to wait for threads $i-1$ and $i+1$ to load values into `buffer`
- synchronization required to avoid race conditions
  - threads have to wait for other threads to fill `buffer`

Launching kernels with shared memory

An additional parameter is added to the launch syntax

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

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

Launch blur kernel with shared memory

```
__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-2;
auto size_in_bytes = n*sizeof(double);

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

Is it worth it?

A version of the blur kernel for arbitrarily large n is provided in `blur.cu` in the example code. The implementation is a bit awkward:

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

The ~10% performance improvement might be worth it, depending on how important the kernel is to overall application performance

Buffering

A pipelined 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

An example is two stencils, applied in order

Double blur: basic OpenMP

```
void blur_twice(const double* in , double* out , int n) {
  static double* buffer = malloc_host<double>(n);

  #pragma omp parallel for
  for(auto i=1; i<n-1; ++i) {
    buffer[i] = 0.25*( in[i-1] + 2.0*in[i] + in[i+1]);
  }
  #pragma omp parallel for
  for(auto i=2; i<n-2; ++i) {
    out[i] = 0.25*( buffer[i-1] + 2.0*buffer[i] + buffer[i+1]);
  }
}
```

Double blur: OpenMP with blocking for cache

```
void blur_twice(const double* in , double* out , int n) {
  auto const block_size = std::min(512, n-4);
  auto const num_blocks = (n-4)/block_size;
  static double* buffer = malloc_host<double>((block_size+4)*
       omp_get_max_threads());

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

  #pragma omp parallel for
  for(auto b=0; b<num_blocks; ++b) {
    auto tid = omp_get_thread_num();
    auto first = 2 + b*block_size;
    auto last = first + block_size;

    auto buff = buffer + tid*(block_size+4);
    for(auto i=first-1, j=1; i<(last+1); ++i, ++j) {
      buff[j] = blur(i, in);
    }
    for(auto i=first, j=2;   i<last;   ++i, ++j) {
      out[i] = blur(j, buff);
    }
  }
}
```

Buffering with shared memory

Shared memory is important for caching intermediate results used in pipelined operations

- shared memory is an order of magnitude faster than global DRAM
- by **fusing** pipelined operations in one kernel, intermediate results can be stored in shared memory
- similar to blocking and tiling for cache on the CPU

Double blur: CUDA with shared memory

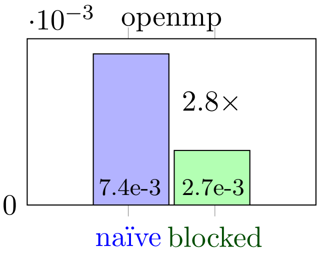
```
__global__ void blur_twice(const double *in, double* out, int n) {
  extern __shared__ double buffer[];

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

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

    __syncthreads();

    out[gi] = blur(li, buffer);
  }
}
```

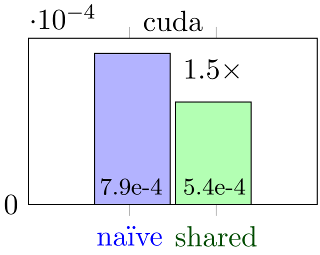
Fused loop results

The OpenMP cache-aware version was harder to implement than the shared-memory CUDA version

- CUDA is initially harder because we have to think and write in parallel from the start

both implementations benefit significantly from optimizations for fast on chip memory





CPU : optimizing for on-chip memory

- let hardware prefetcher automatically manage cache
- choose block/tile sizes so that intermediate data will fit in a target cache (L1, L2 or L3)

GPU : optimizing for on-chip memory

- manage shared memory manually
  - more control
  - hardware-specific
- choose thread block sizes so that intermediate data will fit into shared memory on an SMX

Exercise: Shared Memory

- finish the `shared/string_reverse.cu` example
- implement a dot product in CUDA in `shared/dot.cu`.
  - the host version has been implemented as `dot_host()`
  - assume that n is a power of 2 and $n \leq 1024$
  - **extra**: can you make it work for arbitrary $n \leq 1024$?
  - **extra**: how would you extend it to work for arbitrary $n > 1024$ and n threads?