Distributed and Parallel Computing

Lecture 06

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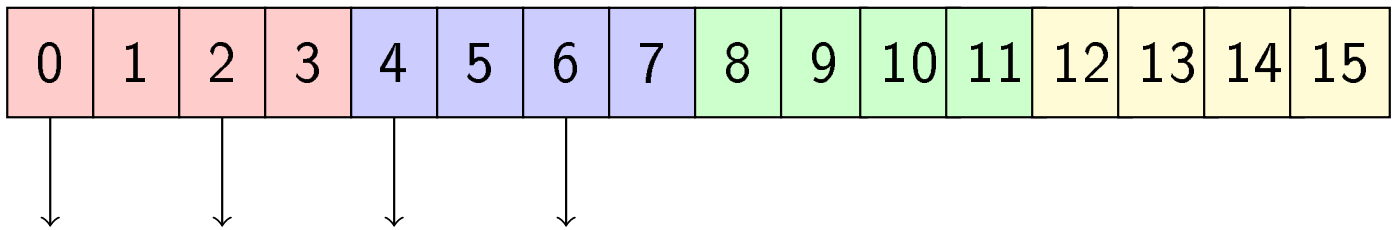
Global Memory Coalescing — Revisited

Global memory is partitioned in **burst sections**

- Whenever a location in global memory is accessed, all other locations in the same section are also delivered
- Burst sections can be 128 bytes or more
- When a warp executes a load or store, the number of dram requests issued (and serialised) is the number of different burst sections addressed
- For example: warp size 4, burst size 16 bytes (4 words), stride=2: 2 memory transactions required



- Order of access doesn't matter

Shared Memory Bank Conflicts — Revisited

Shared memory is stuctured into **banks**

- Modern GPUs have 32 4-byte word banks but can be configured as 32 8-byte double word banks
- The bank used for a word address is the remainder when you divide the word address by the number of banks
- Shared memory can deliver/accept 1 word simultaneously from each bank in a single read/write transaction
- Multiple accesses to the same bank are serialized
- For example: warp size 4, 4 banks, 32 words:
  - Warp accesses (00, 01, 02, 03) or (00, 05, 10, 15) in 1 op
  - Warp accesses (00, 02, 04, 06) in 2 ops, (00, 04, 08, 12) in 4

00	01	02	03
04	05	06	07
08	09	10	11
12	13	14	15

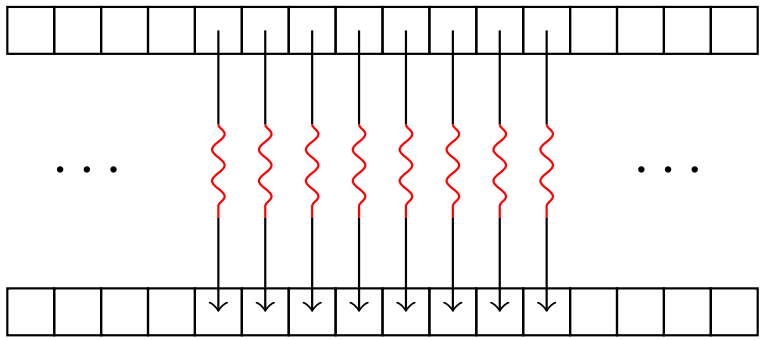
General Parallel Programming Patterns

There are a number of standard parallel programming patterns that form the basic building blocks of most GPU programs:

- Map
- Gather
- Scatter
- Stencil
- Transpose
- Reduce
- Scan/Sort
- Histogram

Map

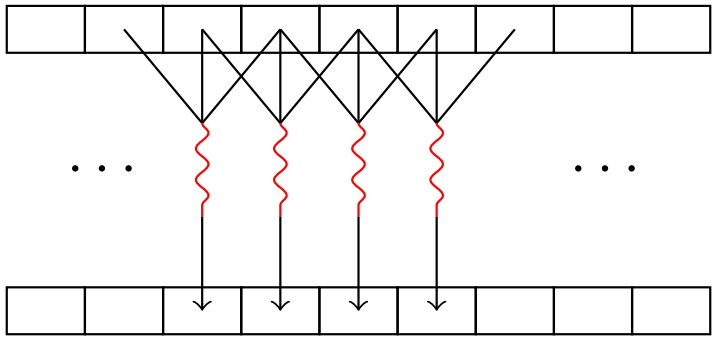
Map uses each thread to take an input value from the location corresponding to the block/thread id and write an output value to the location corresponding to the block/thread id with no two threads reading from or writing to the same location.



- One-to-one pattern
- No read/write race issues if source and destination are different
- Easy to ensure coalesced global memory accesses
- Easy to avoid shared memory bank collisions

Gather

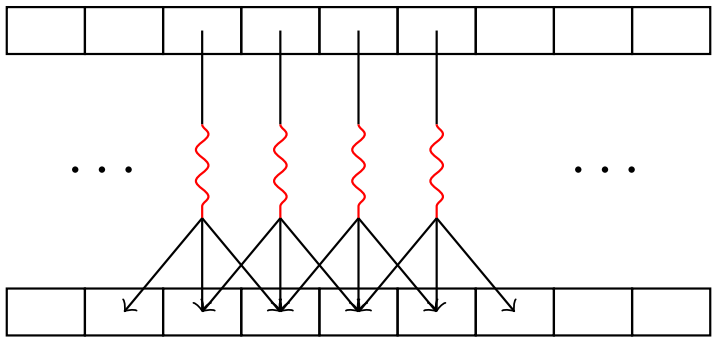
Gather uses each thread to take one or more input value from some locations (not just one from the direct location indicated by the thread and block id) and write an output value to one location with no two threads writing to the same location. Multiple different threads may share some read locations.



- Gather locations may have different patterns for each thread
- Many-to-one pattern
- No read/write race issues if source and destination are different
- Easy to ensure coalesced global memory accesses on writes
- Easy to avoid shared memory bank collisions on writes
- Care needed on read access patterns

Scatter

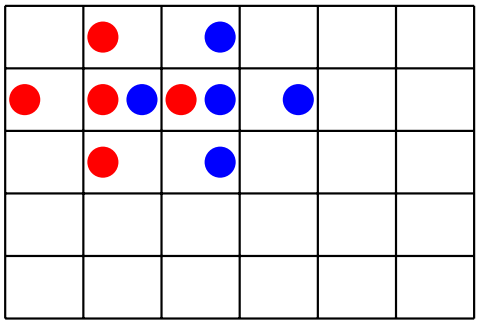
Scatter uses each thread to read the value from the location corresponding to the block/thread id and write output values to a number of locations Multiple different threads may share some write locations (e.g. using read/write operations such as increment)

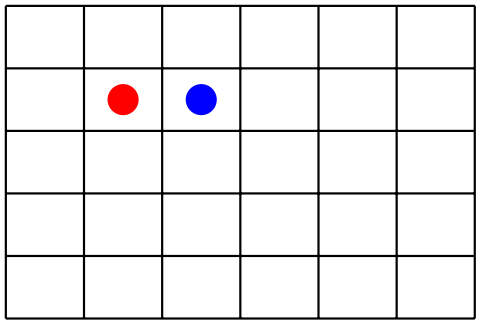


- Write locations may have different pattern for each thread
- One-to-many pattern
- Potential overwrite race issues
- Easy to ensure coalesced global memory accesses on reads
- Easy to avoid shared memory bank collisions on reads
- Care needed on write access patterns

Stencil

Stencil is a special case of Gather where the pattern of reads is constant across the threads.





- Read locations have the same pattern for each thread
- Several-to-one pattern
- No read/write race issues if source and destination are different
- Easy to ensure coalesced global memory accesses on writes
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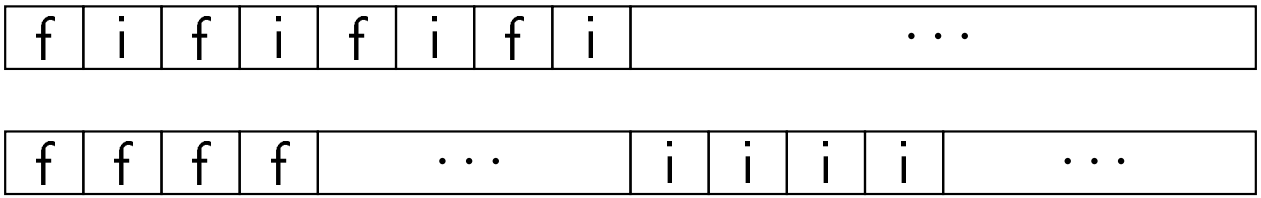
- Care needed on read access patterns

Transpose

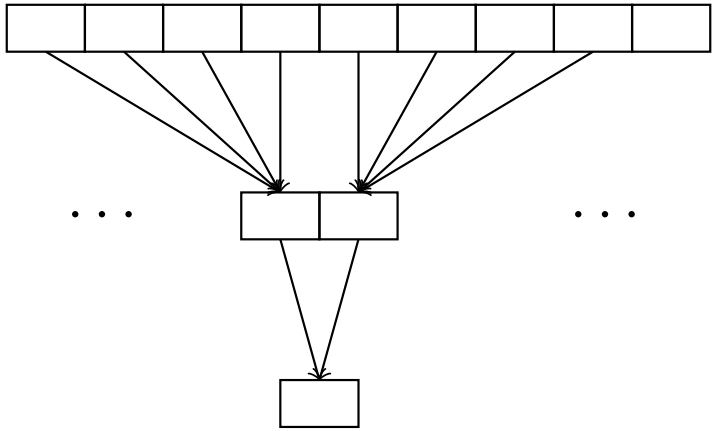
Transpose is most commonly the standard transpose operation on matrices, but is also used for restructuring datastructures for efficient memory accesses.

```
struct {
    float f;
    int i;
} X[LEN];
```



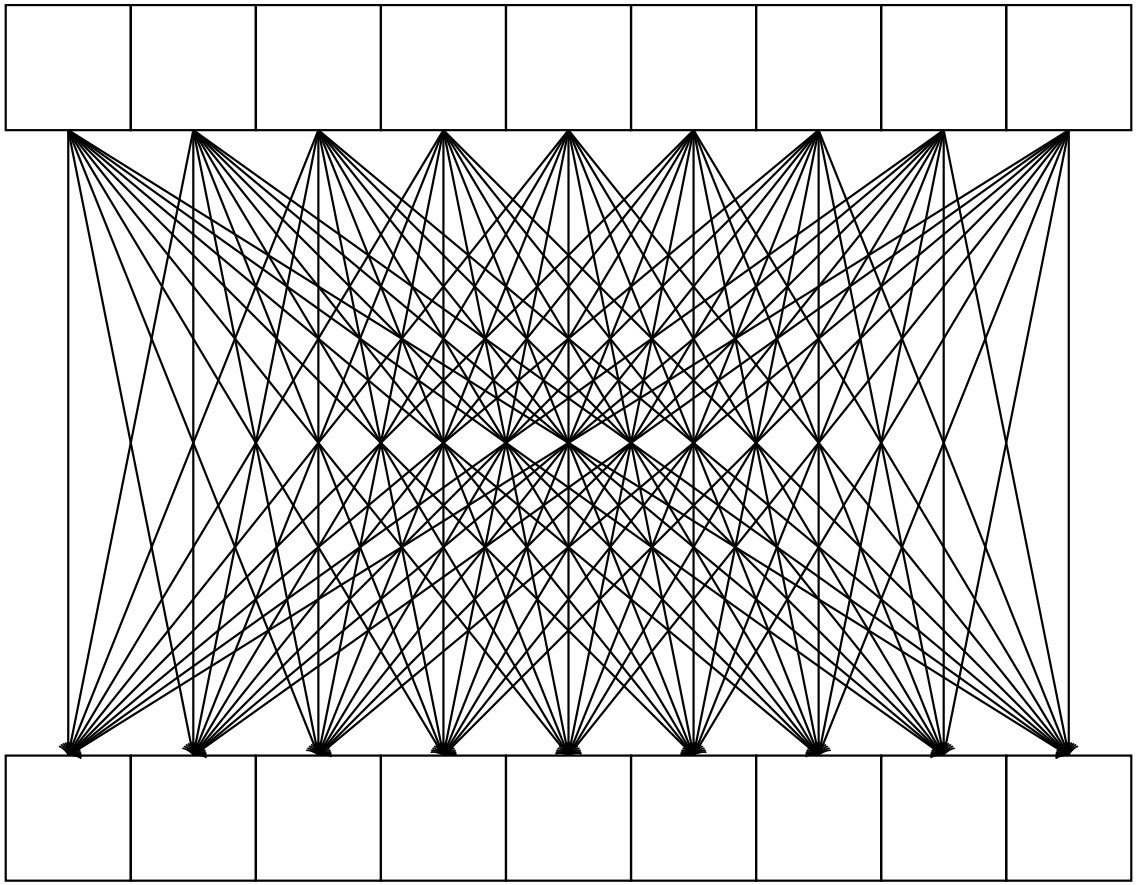
- Can be implemented with a *Scatter* or with a *Gather*

Reduce



- Many-to-one

Scan/Sort



- All-to-All (or at least Many-to-All)

Histogram — Serial Version

```
for (i=0; i < NUM_BINS; i++)
    bin[i] = 0;
for (i=0; i < NUM_VALS; i++)
    bin[computeBin(vals[i])] ++;
```

Histogram — Parallel Version (with error)

```
__global__ void hist(int *d_bins, const int *d_vals,
                     const int NUM_BINS)
{
    int id =  blockDim.x * blockIdx.x + threadIdx.x ;
    int val = d_vals[id] ;
    int bin = val % NUM_BINS; // computeBin function

    d_bins[bin]++ ;
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- Scalability?
- 1M values $\Rightarrow$ 1M atomic adds

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