

Automated architecture-aware mapping of streaming applications onto GPUs

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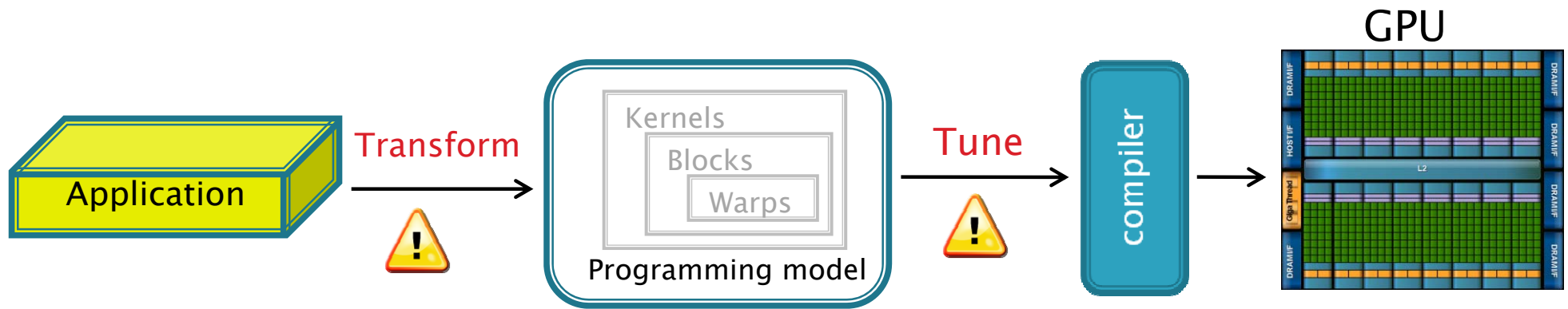
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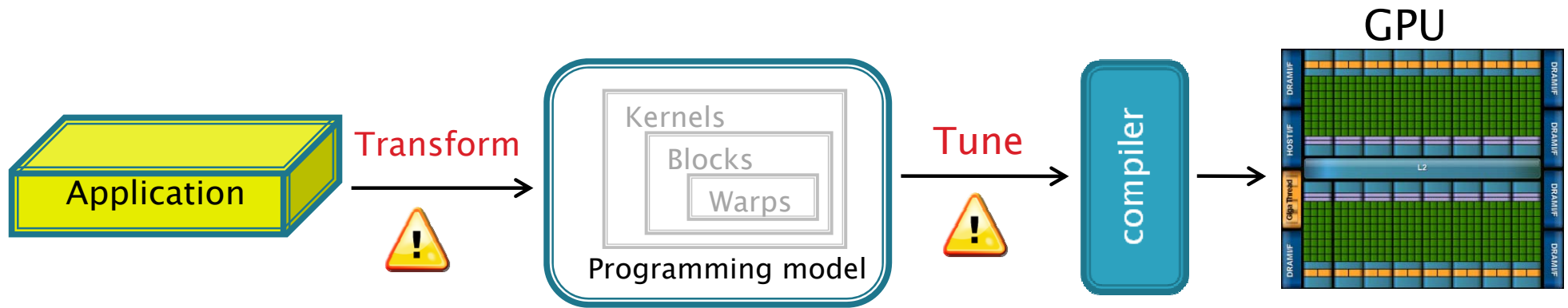


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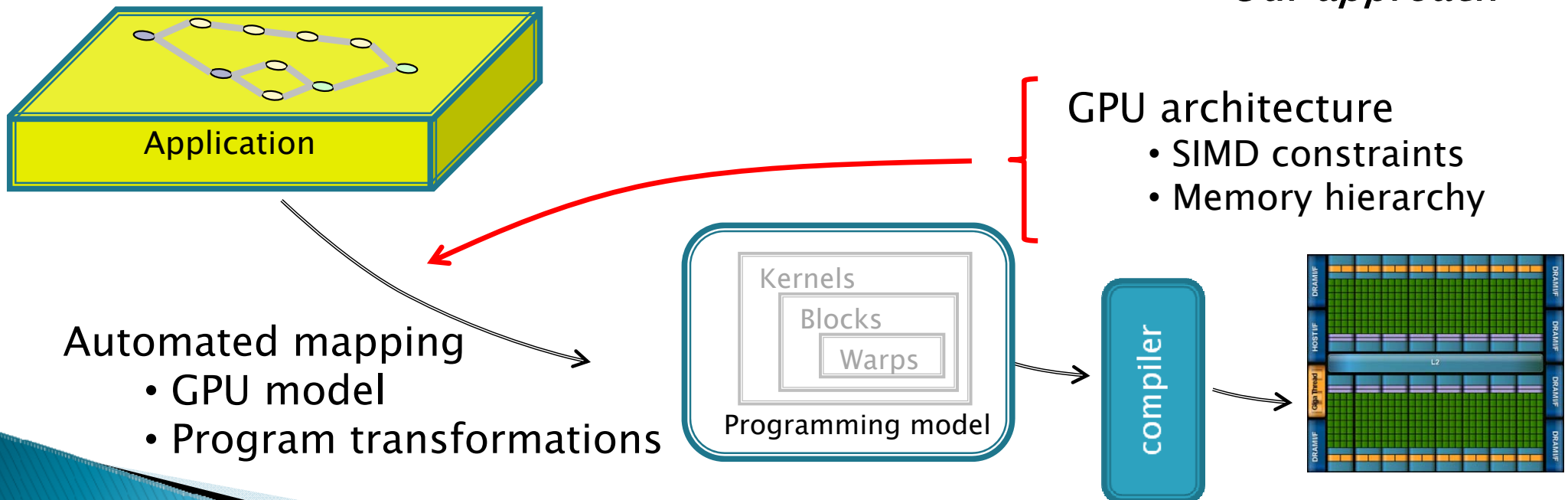
Overview



Overview

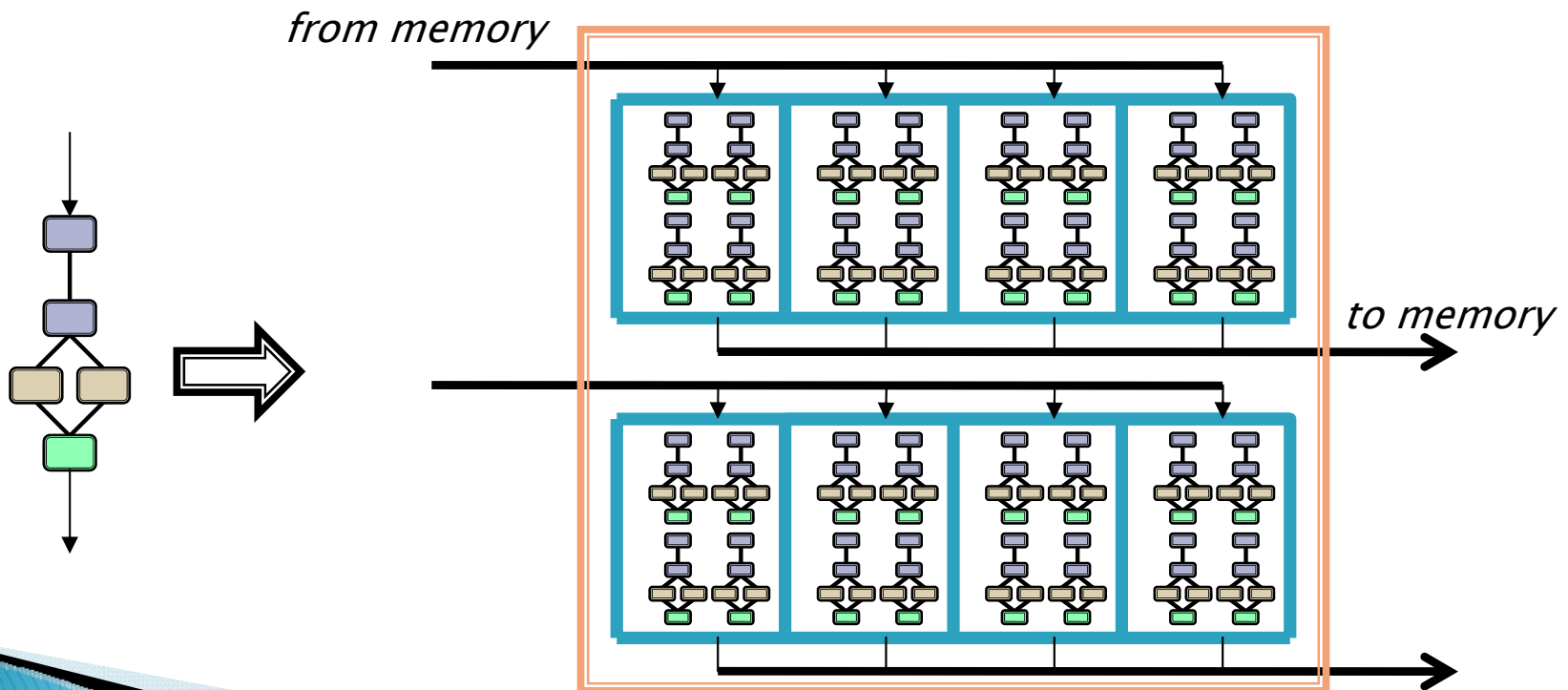


Our approach



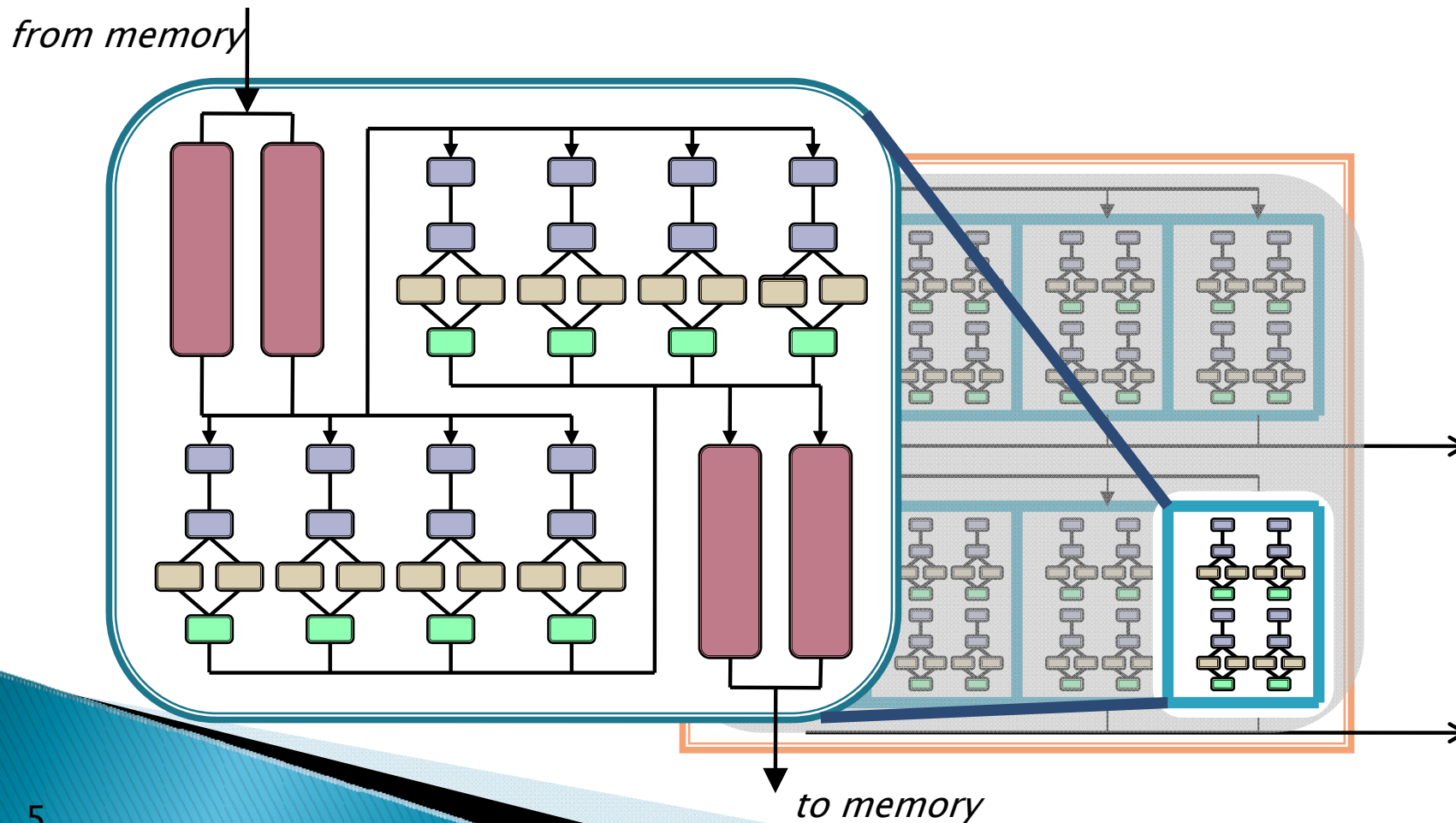
Our mapping strategy

① Stream graph \rightarrow Parallel instances of the entire graph



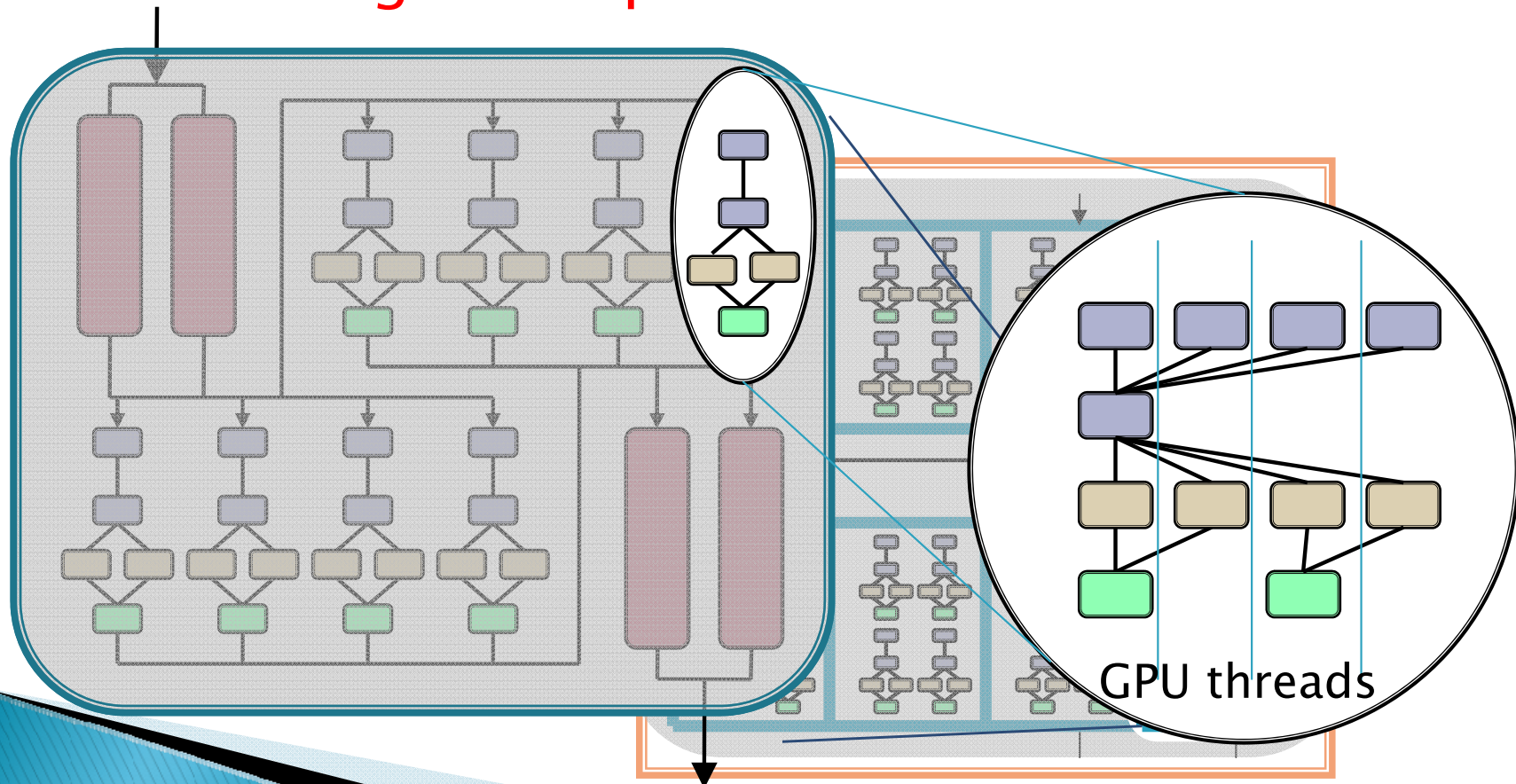
Our mapping strategy

- ① Stream graph \rightarrow Parallel instances of the entire graph
- ② **Novel memory access scheme**



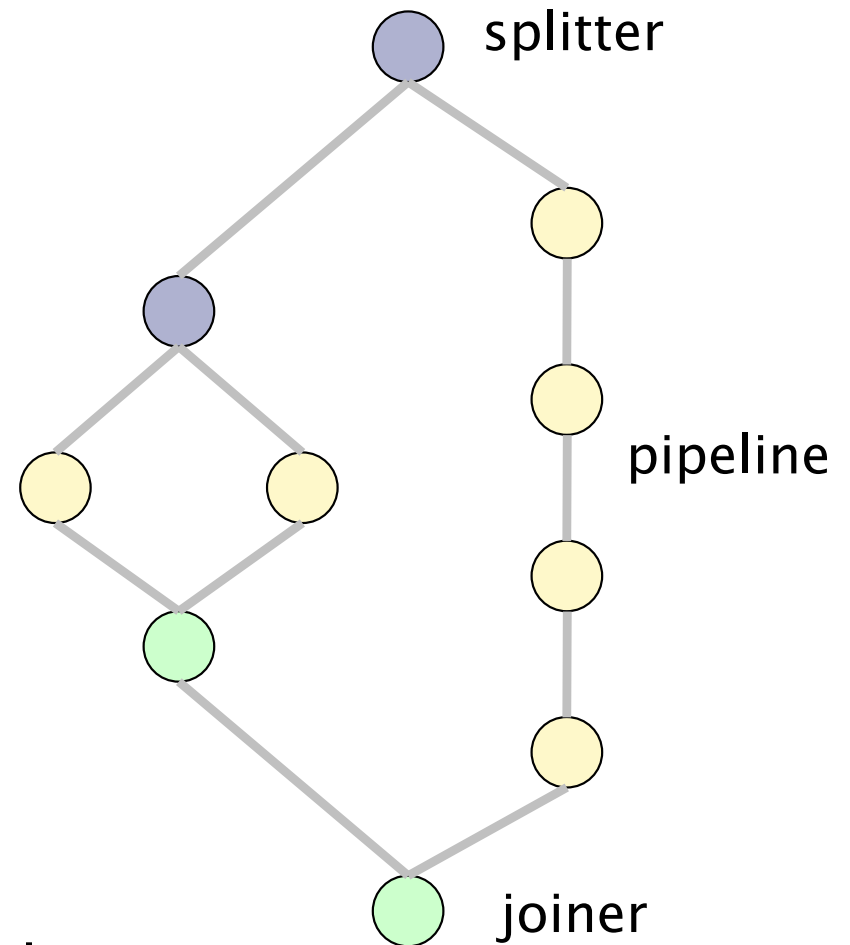
Our mapping strategy

- ① Stream graph \rightarrow Parallel instances of the entire graph
- ② Novel memory access scheme
- ③ Utilize fine-grained parallelism



StreamIt

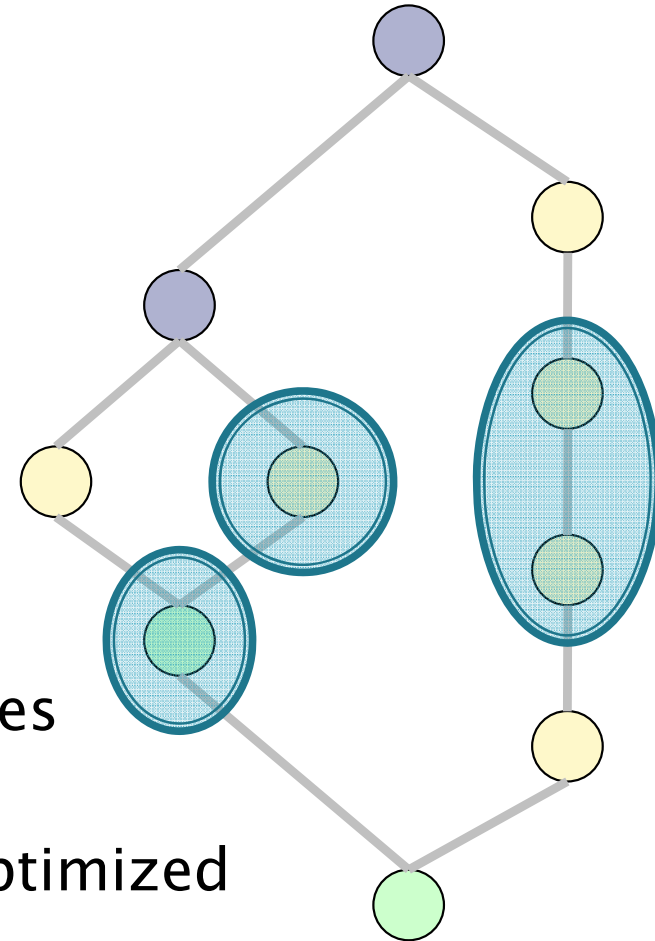
- ▶ Hierarchical stream graph
 - Well defined rates
 - Pipeline
 - Splitters / Joiners
 - Mostly *stateless* filters
- ▶ StreamIt compiler
 - Schedules
 - Flattens
 - Analyzes
- ▶ Peeking
 - Alternative to filters with state
 - Allows access to input consumed by future iteration



Stream graph

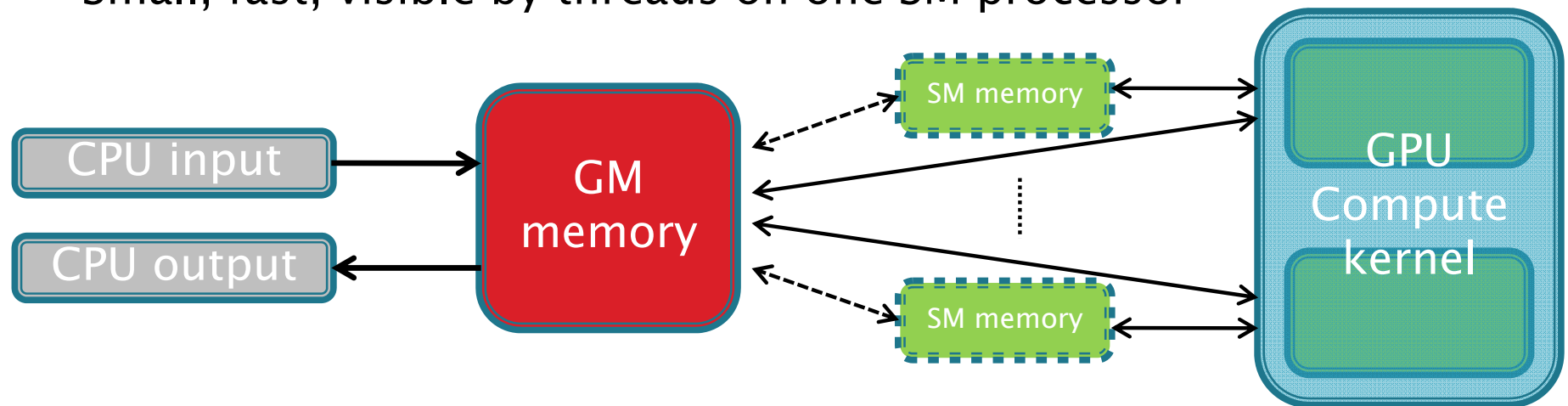
Related work on StreamIt to GPU

- ▶ Udupa et al. (CGO 2009)
 - Software pipelined execution of stream programs on GPUs
 - ⚠ no memory prefetching
 - ⚠ pipeline computation
- ▶ Hormati et al. (ASPLOS 2011)
 - Sponge: Portable Stream Programming on Graphics Engines
 - ✓ memory access scheme
 - ⚠ memory traffic not fully optimized (filters fused partially)
 - ⚠ no compression on multiple threads



GPU memory hierarchy

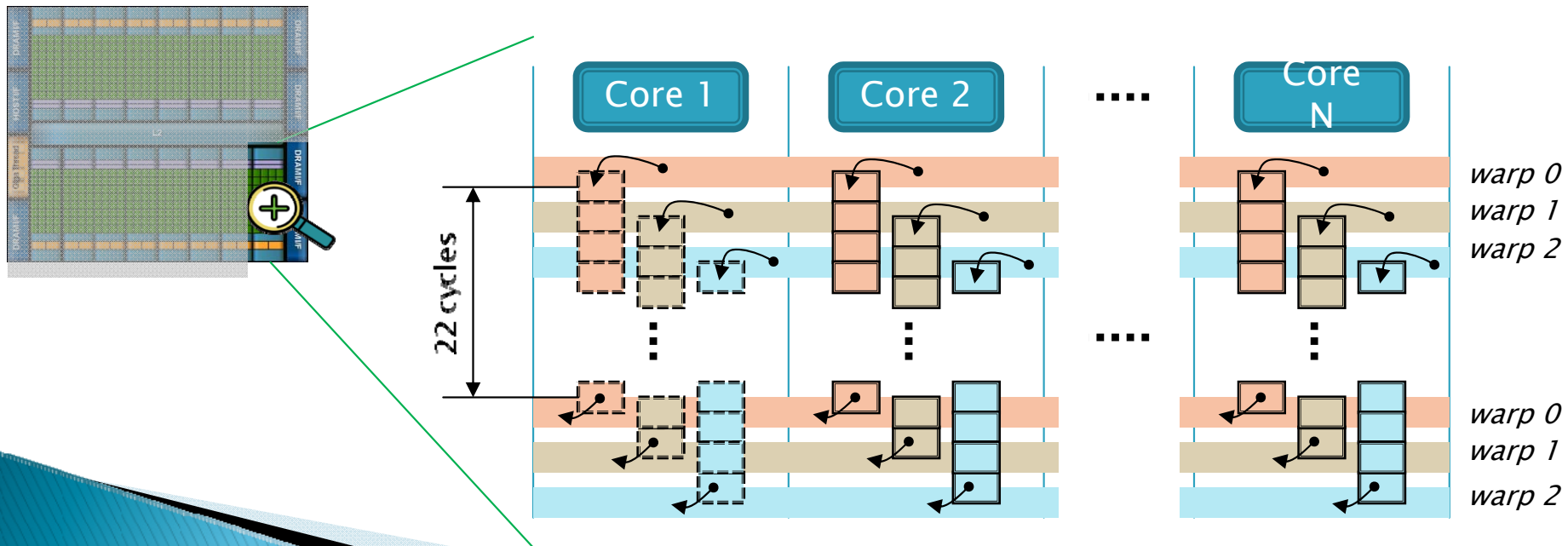
- ▶ **Global GM memory**
 - Large, slow, visible by threads on all SM processors
- ▶ **Shared SM memory**
 - Small, fast, visible by threads on one SM processor



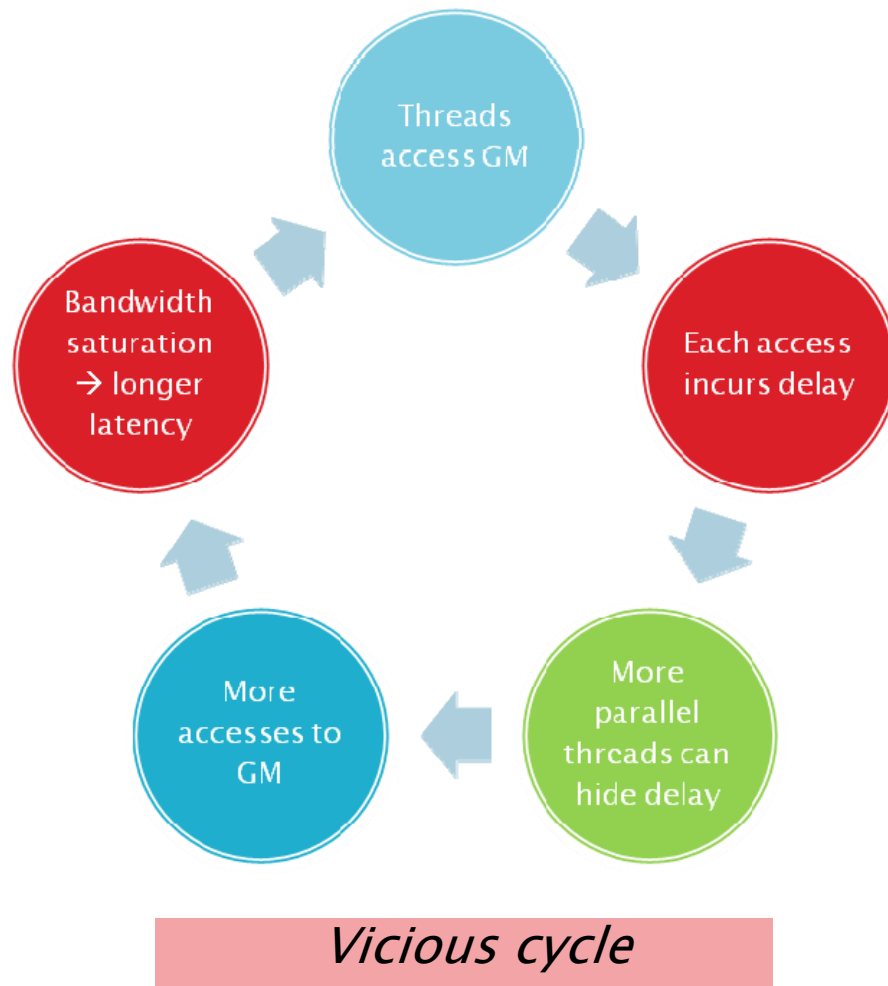
- ▶ **Other memories, subset of GM**
 - Local memory – for registers spilling
 - Texture memory – different access pattern

GPU internals

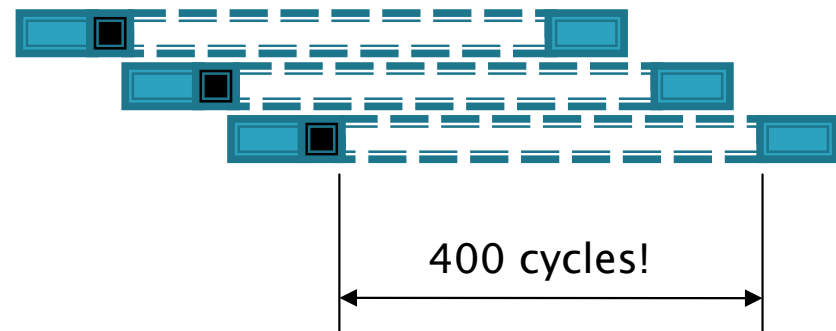
- ▶ Array of SIMD processors (SM processors)
 - Each handles a large pool of threads grouped in *warps*
- ▶ Interleaved execution for high throughput
 - operation latency (22 cycles)
 - memory latency (~ 400 cycles) ⚠



Memory access pattern



- ▶ Influenced by ratio of:
 - Memory access
 - Computation
- ▶ Bandwidth limitation



Specialization

- ▶ Workset: GM memory or SM memory?
 - GM → many parallel threads
 - saturate bandwidth
 - SM → prefetching
 - Requires parallel loads / stores
 - SM memory size dictates number of parallel iterations
 - prefetch rate linked to workset size
-
- ▶ Separate GM memory accesses from computation
 - **Specialize warps**
 - Use SM memory to cache the workset
 - Computation-only warps **release the workset faster**

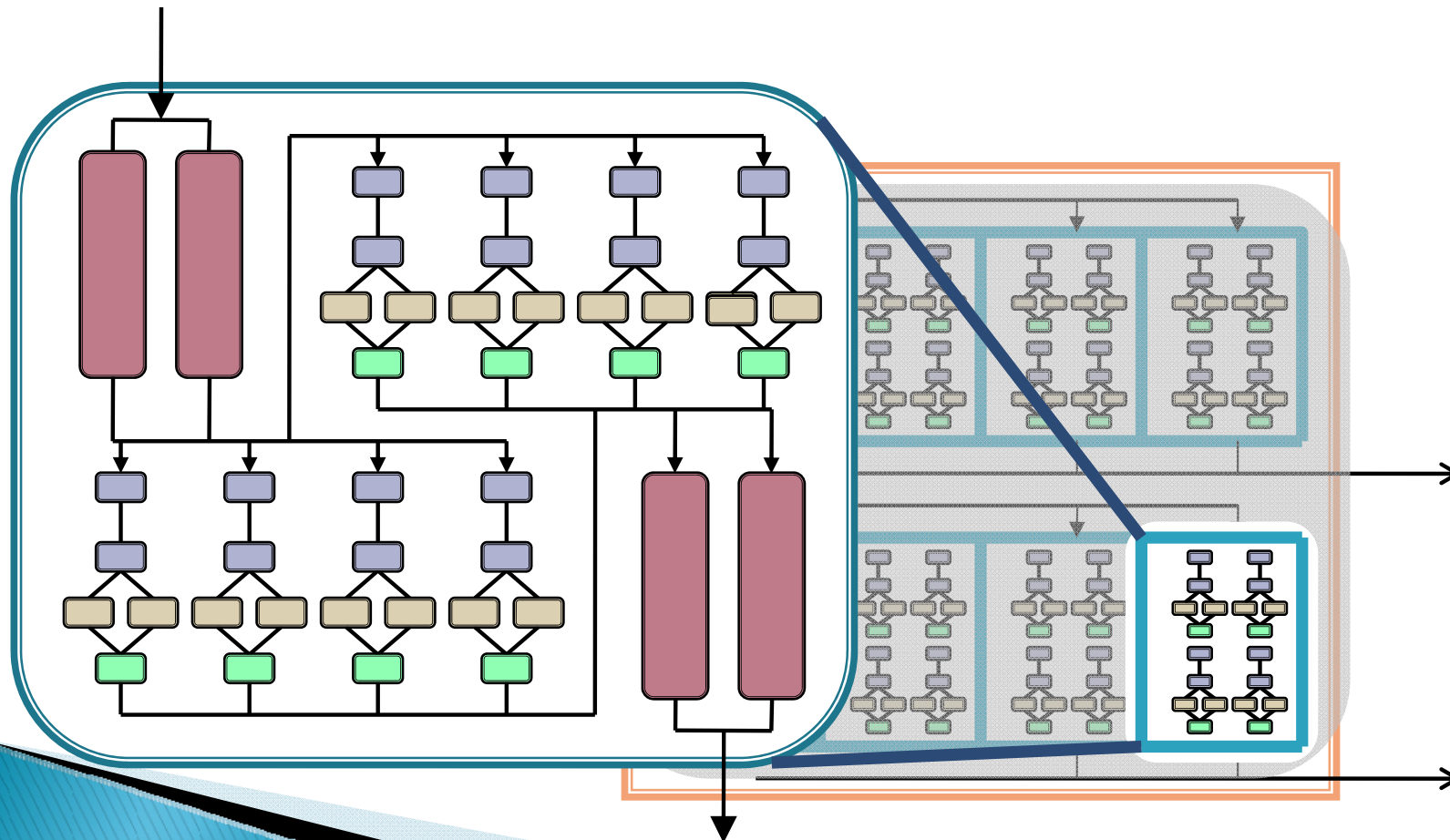


Mapping strategy

Stream graph \rightarrow Parallel instances of the entire graph

Novel memory access scheme

Utilize fine-grained parallelism



SIMT versus SIMD

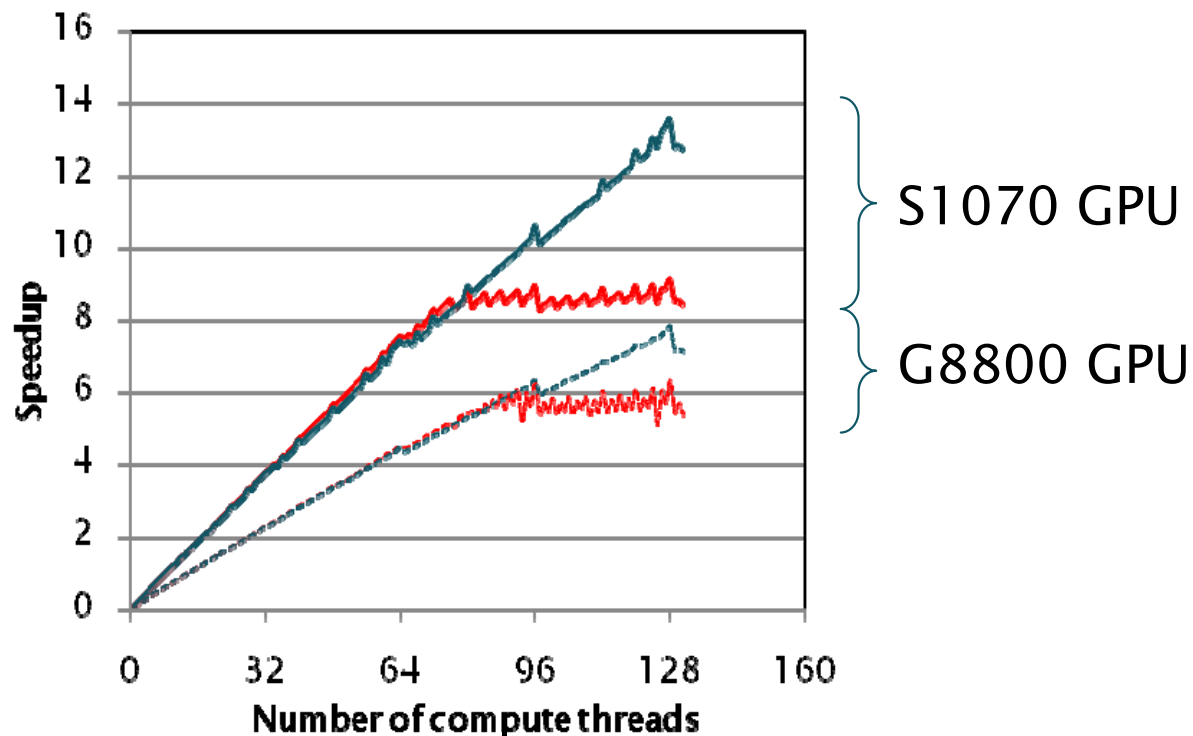
- ▶ Misconception: Threads should not diverge
 - True only for threads belonging to a warp
- ▶ Warp:
 - SIMD execution model
 - Static thread allocation (based on thread ID)

- ▶ No penalty for this CUDA code:

```
if (threadIdx.x < warpSize) {  
    compute_action();  
} else if (threadIdx.x >= warpSize && threadIdx.x < 2 * warpSize)  
    memory_access_action();  
} else if ...
```

Bandwidth limitation

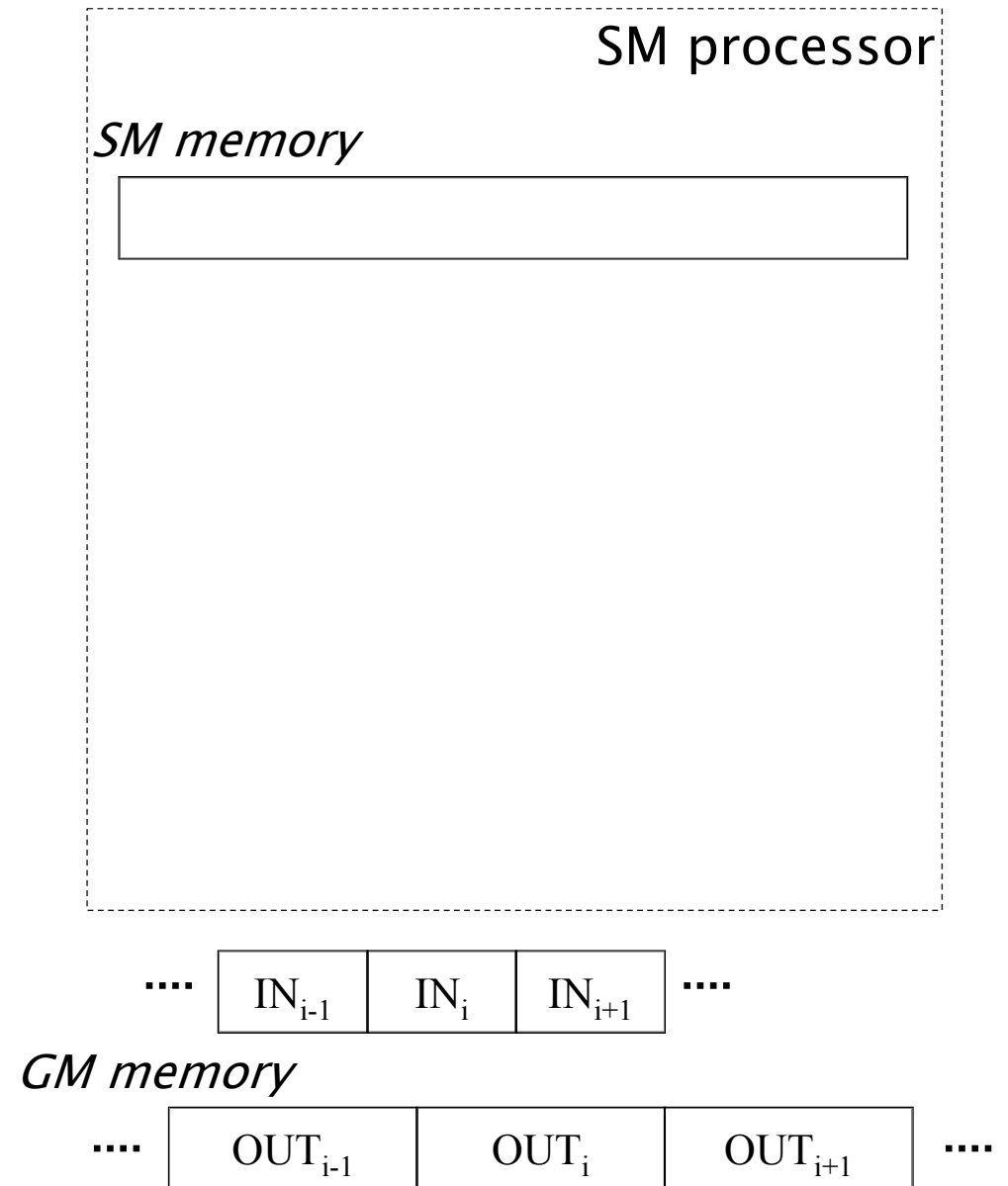
- ▶ Insufficient memory access warps limit performance



- Insufficient to sustain required bandwidth
- Additional warps for memory access

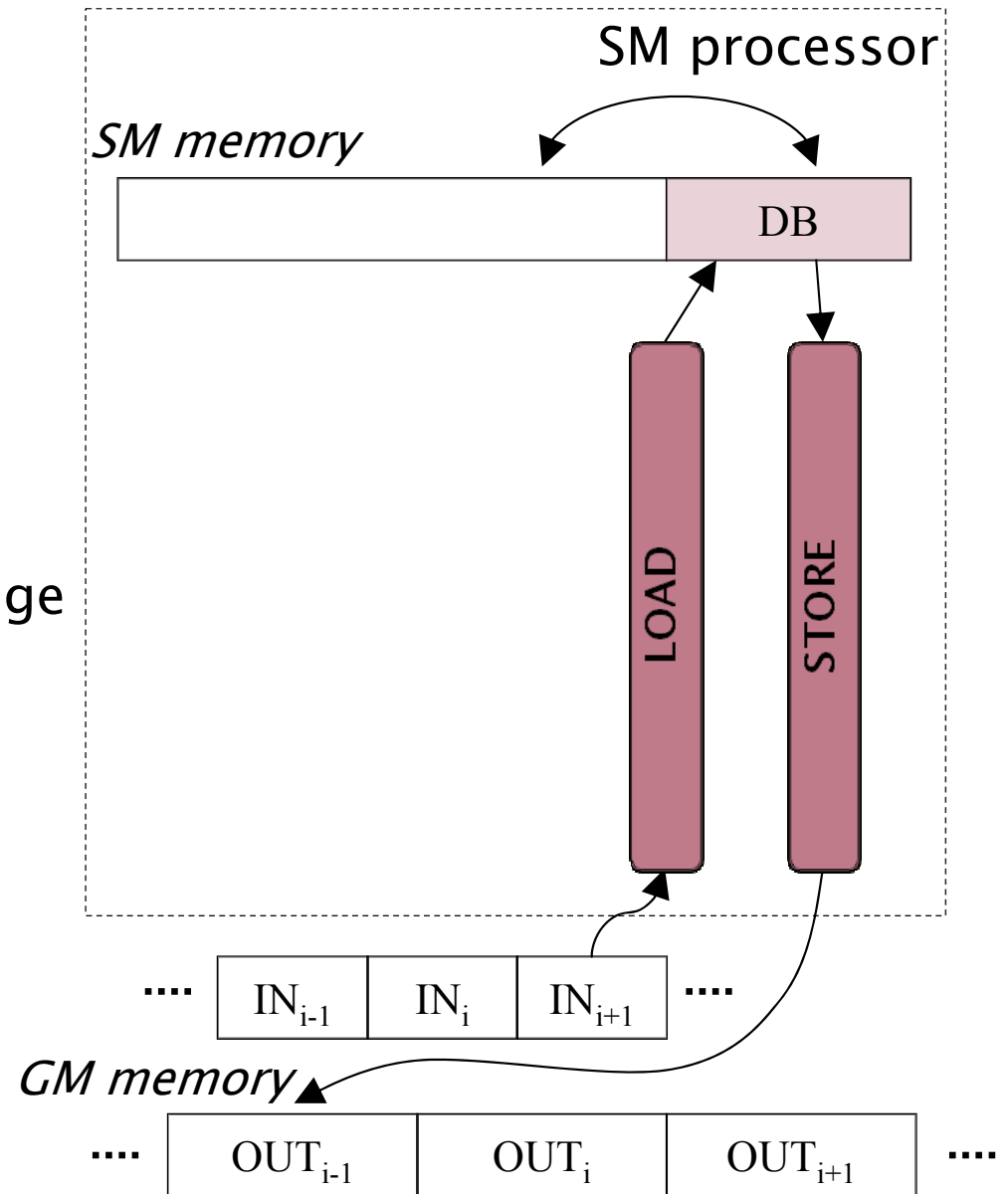
Data movement

- ▶ Software pipelining a group of iterations in each SM processor
- ▶ I/O streams in GM memory



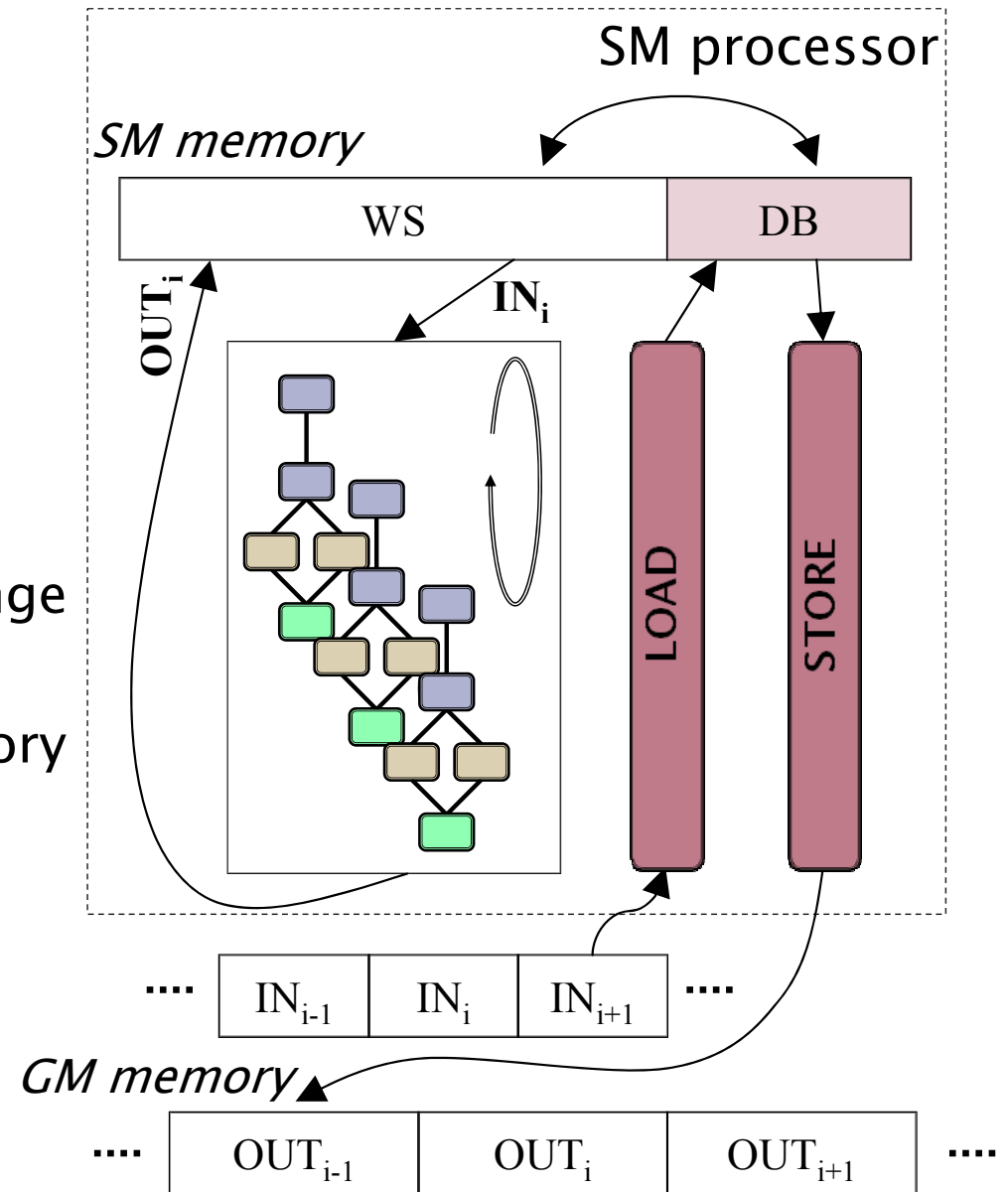
Data movement

- ▶ Software pipelining a group of iterations in each SM processor
- ▶ I/O streams in GM memory
- ▶ Double buffer (DB) for I/O exchange



Data movement

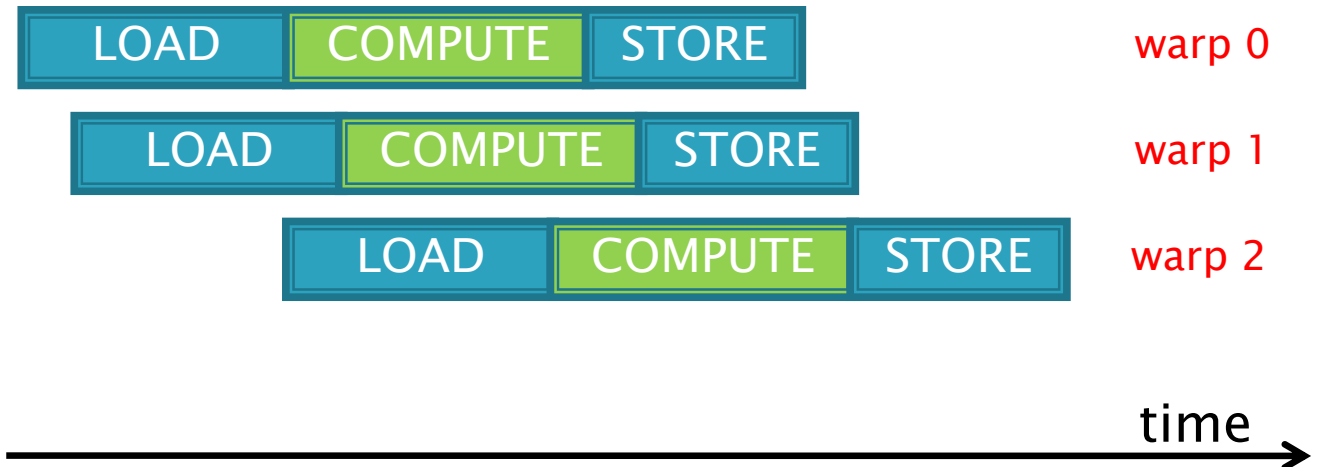
- ▶ Software pipelining a group of iterations in each SM processor
- ▶ I/O streams in GM memory
- ▶ Double buffer (DB) for I/O exchange
- ▶ Workset (WS) must fit in SM memory
 - I/O data
 - All intermediate stream data
 - ➔ Limited number of iterations



Prefetching vs Specialization

Prefetching

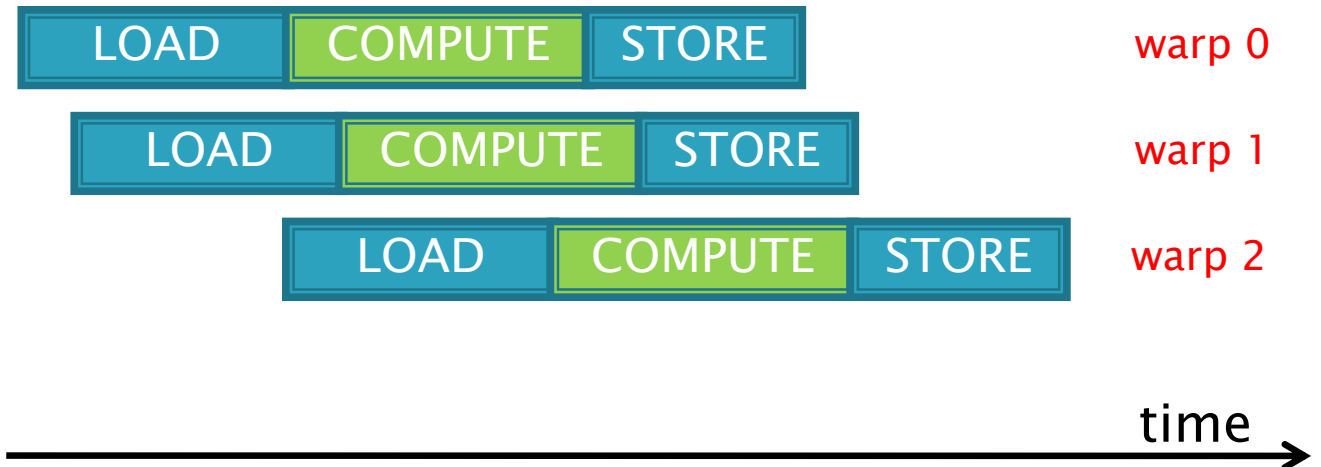
- 3x COMPUTE warps
- 3x WS memory



Prefetching vs Specialization

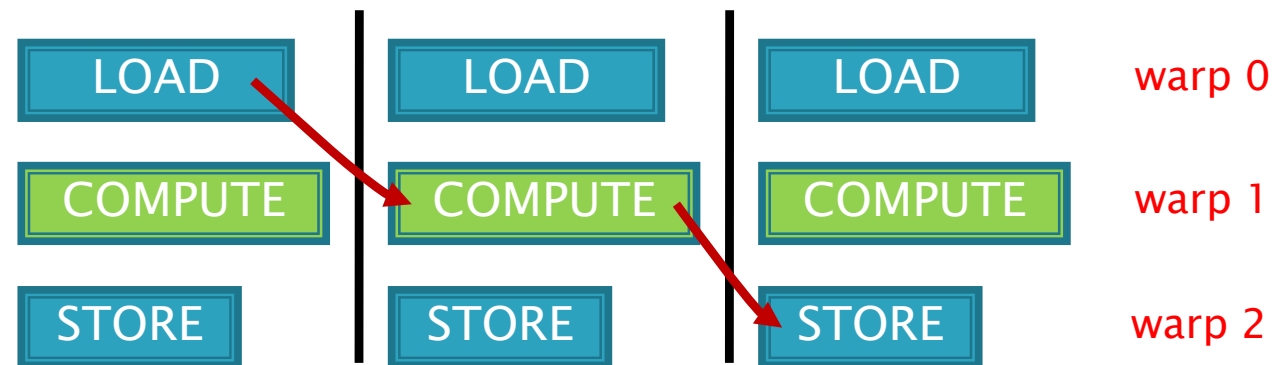
Prefetching

- 3x COMPUTE warps
- 3x WS memory



Specialization

- 1x COMPUTE warp
- 1x (WS+DB) memory

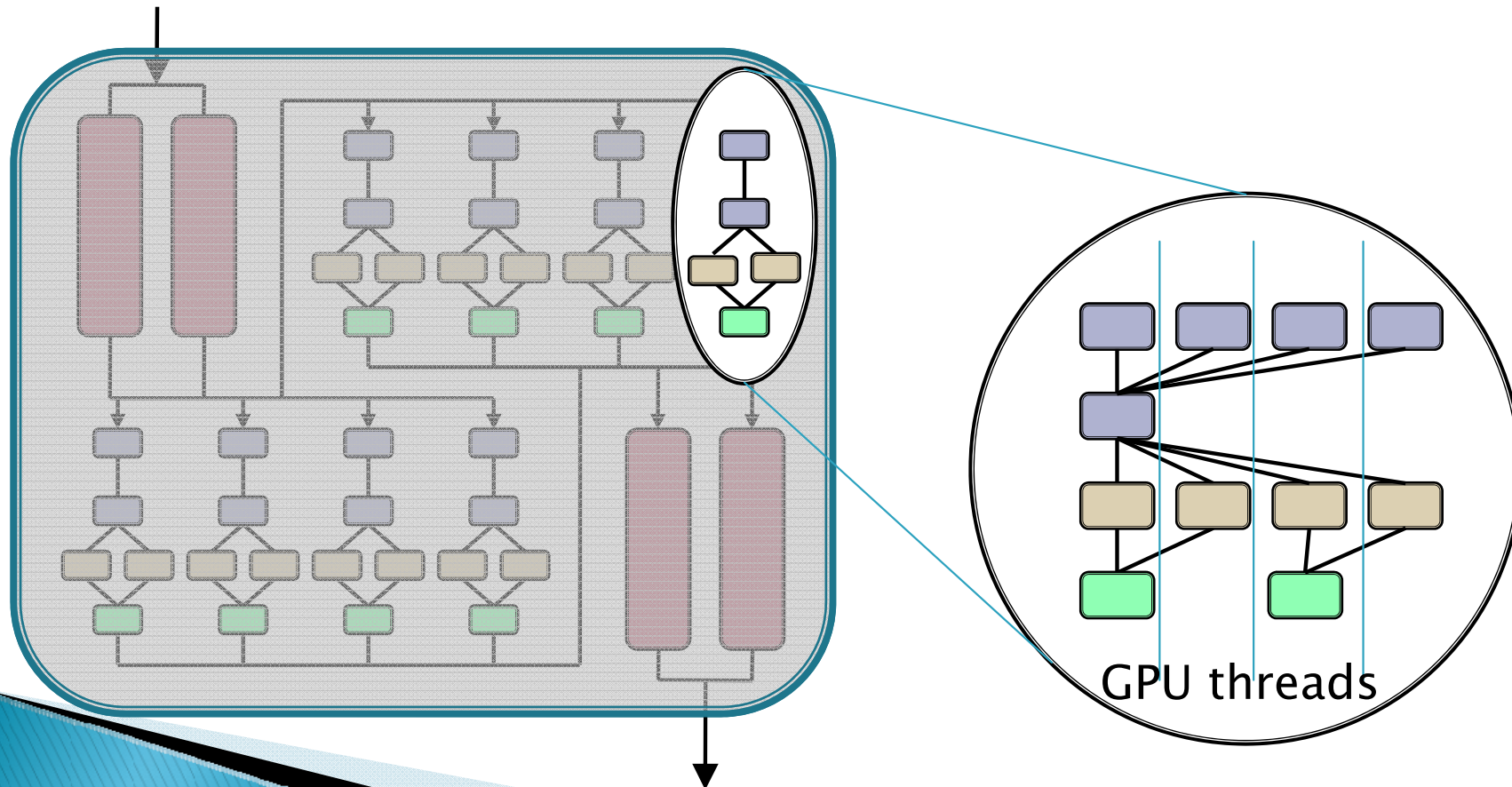


Mapping strategy

Stream graph \rightarrow Parallel instances of the entire graph

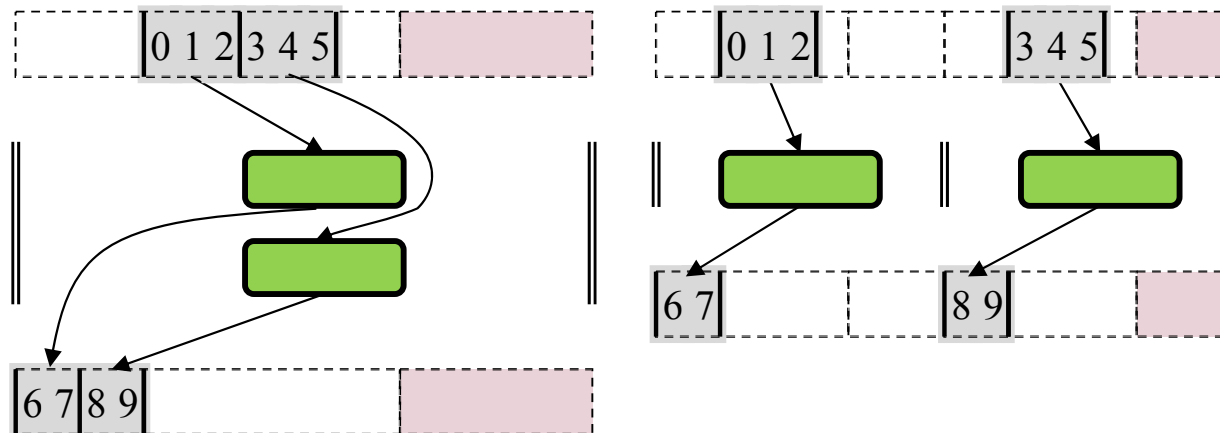
Novel memory access scheme

Utilize fine-grained parallelism

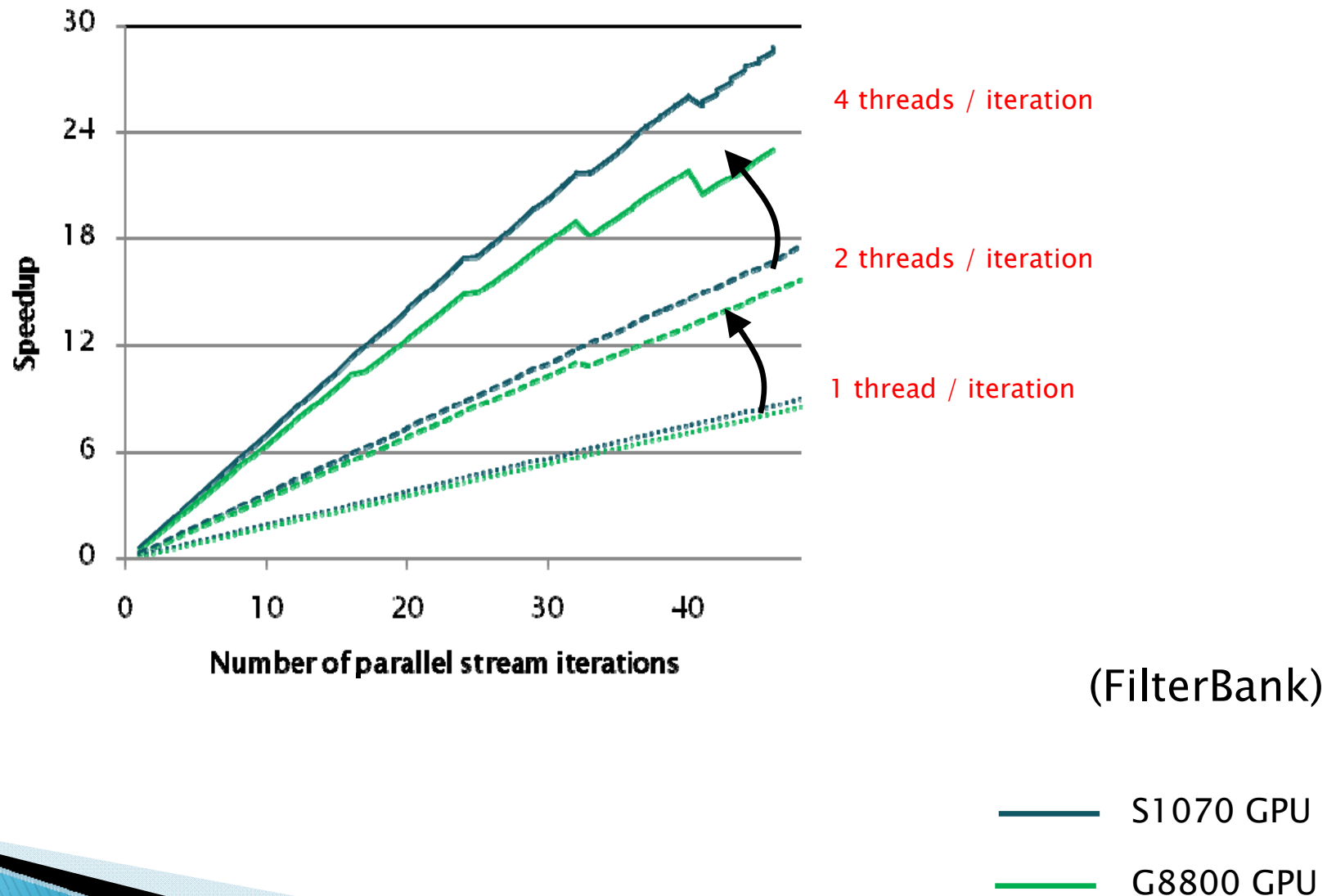


Fine grained parallelism

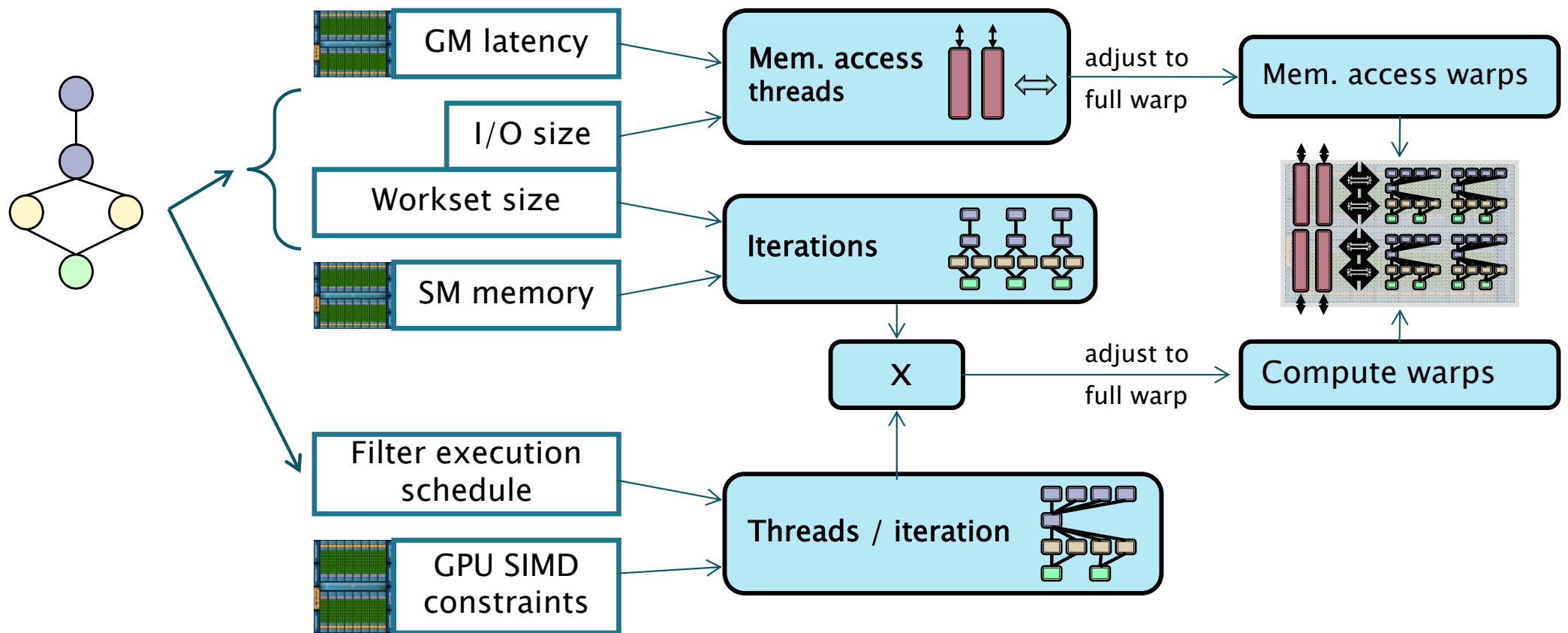
- ▶ Multiple threads / stream iteration
 - Distributed schedule
- ▶ Synchronization
 - Lock-step execution of warp threads



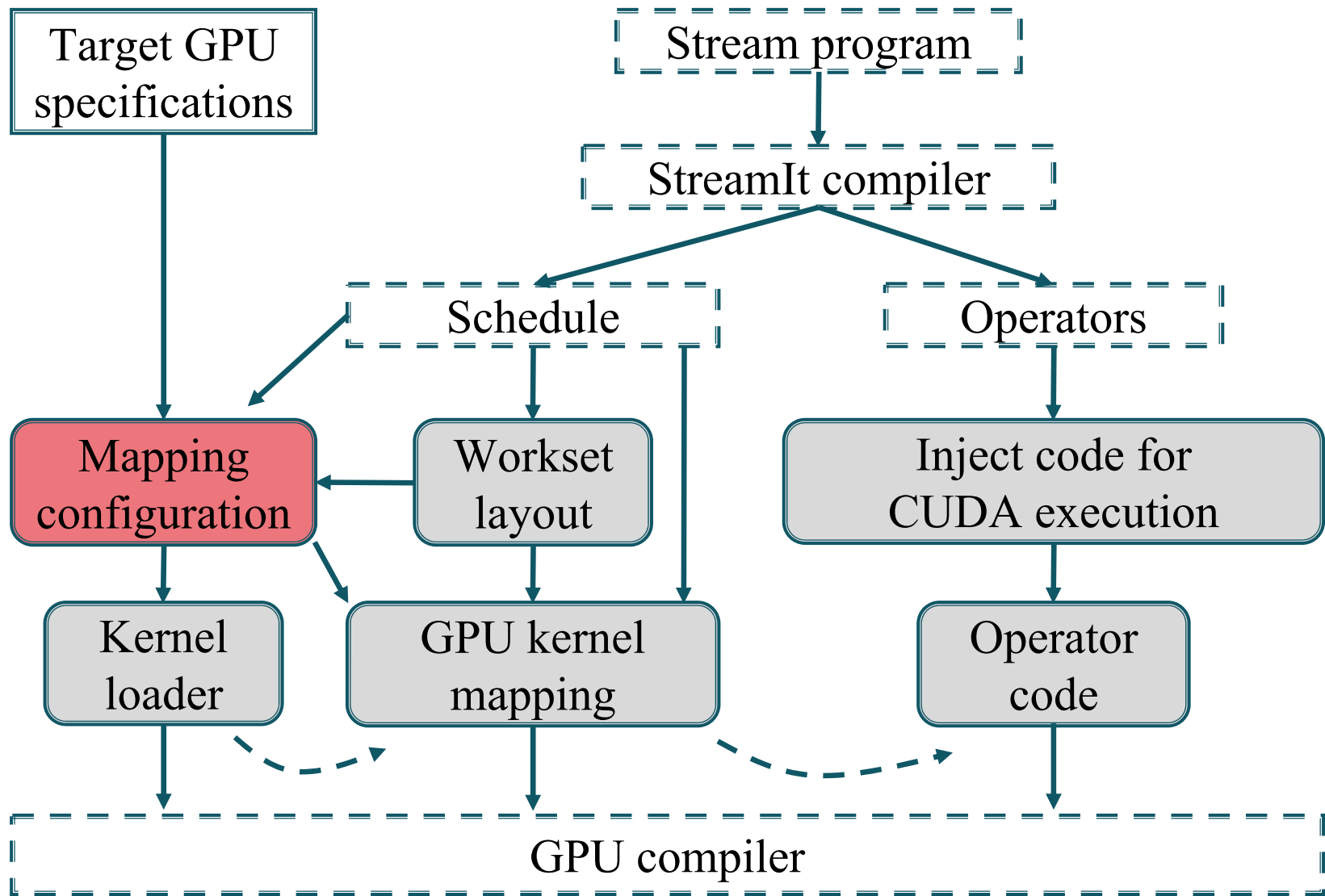
Design space characterization



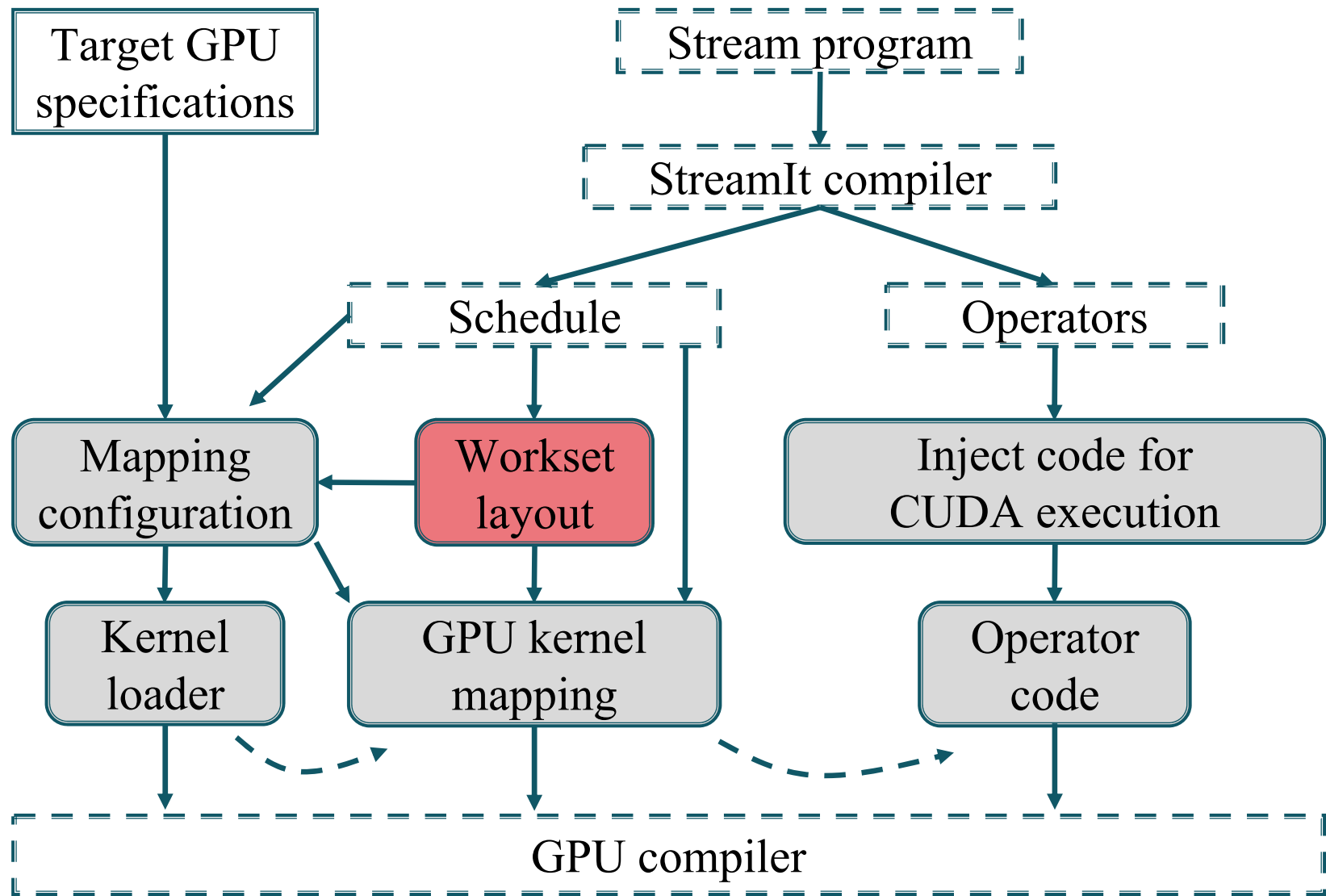
Design point selection



Flow



Flow



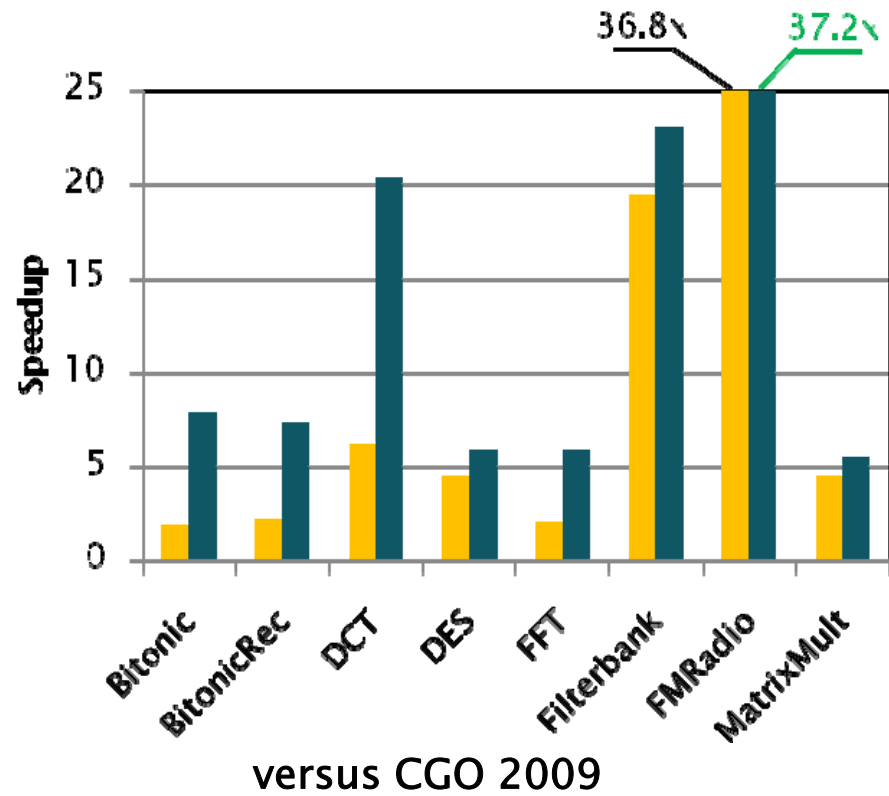
Workset layout

- ▶ Fragmentation of workset allocation
 - Small buffers are required between filters
 - Liveness analysis → estimation of workset size
 - Fragmentation → actual allocation may lead to a slight increase
- ▶ Coalesced memory access

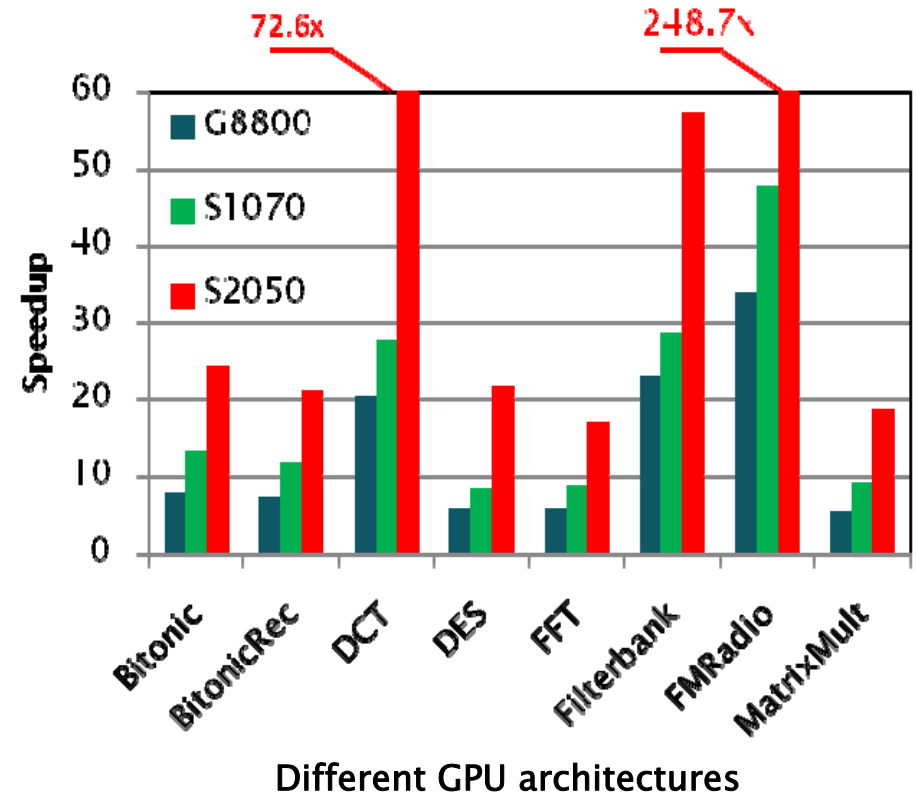
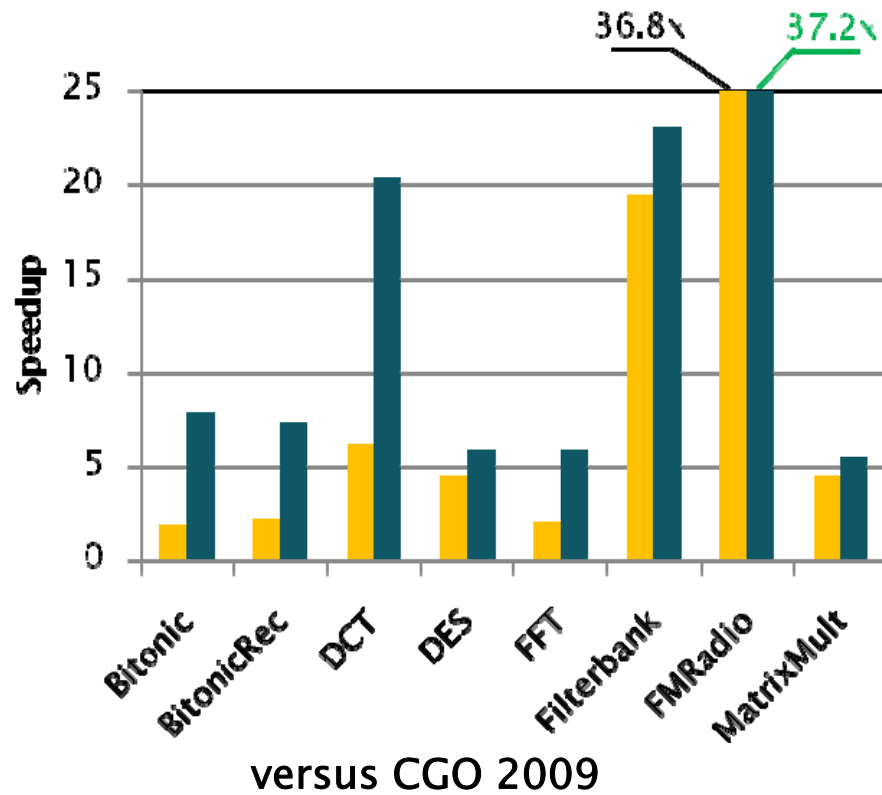
Peeking

- ▶ Inter-iteration dependencies
- ▶ Overlap input data to reconstruct the initial elements
 - For each SM processor
 - For each parallel thread group
- ▶ Intuition:
 - Warm-up intermediate buffers
 - Threads access previous iterations
- ▶ Custom synchronization
 - Only between compute threads
 - Implemented custom barrier

Results



Results



Conclusions

- ▶ Novel scheme to execute stream graphs on GPU
- ▶ Automatic heuristic for selecting efficient design points
- ▶ Novel memory access scheme through software pipelining

Thank you

- ▶ Questions?