Improving SIMD Efficiency for Parallel Monte Carlo Light Transport on the GPU

by Dietger van Antwerpen

Outline

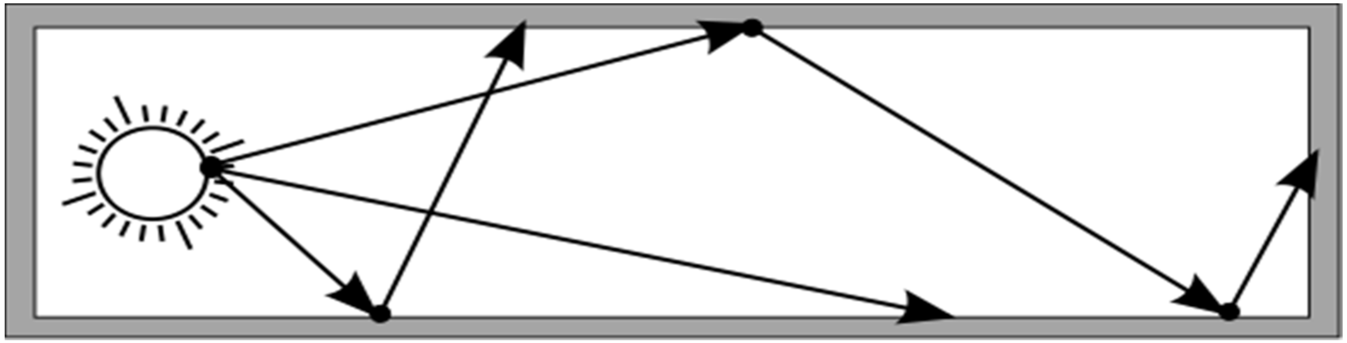
- **Introduction**
- Path Tracing
- Bidirectional Path Tracing
- Metropolis Light Transport
- Results
- Demo

Parallel MC Rendering

- Monte Carlo rendering embarrassingly parallel
- Generate many samples in parallel
- Not so trivial for wide SIMD architectures
- Samples have **stochastic sample length**
- Uneven sample workload
- Incoherent execution flow
- Low SIMD efficiency

Random Walk

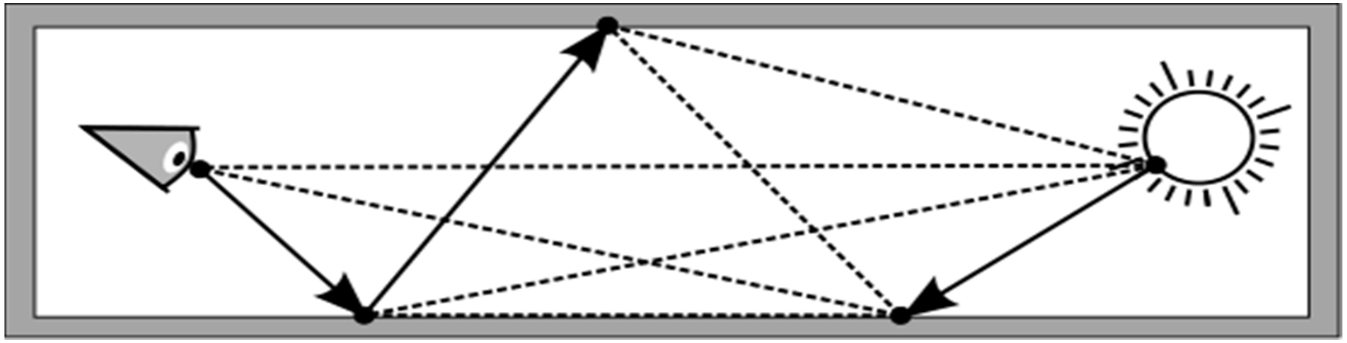
- PT and BDPT use random walks



- Walk is terminated using Russian roulette
- Stochastic path lengths
- ~**33% active threads** per GPU warp
- **Upper bound** on SIMD efficiency

Bidirectional Connections

- BDPT fully connects two random walks



- Number of connections is **quadratic** in average random walk length
- ~**17% active threads** per GPU warp
- Upper bound on SIMD efficiency

Contributions

- Improving average SIMD efficiency
  - *Random walk phase*:

    Combining **stream compaction** and **sample regeneration**
  - *Bidirectional connect phase*:

    Evaluating all **connections** from all samples **in parallel**

- Implement **MLT** on top of BDPT on the GPU

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In-Place Sample Regeneration

- Proposed by Novak et al.
- Regenerate after each extension
- **Restart** all **terminated samples in-place**
- Advantage:
  - Improves SIMD efficiency during sample extension and connection
- Disadvantage:
  - Low SIMD efficiency during regeneration
  - ~**30% active threads** per GPU warp

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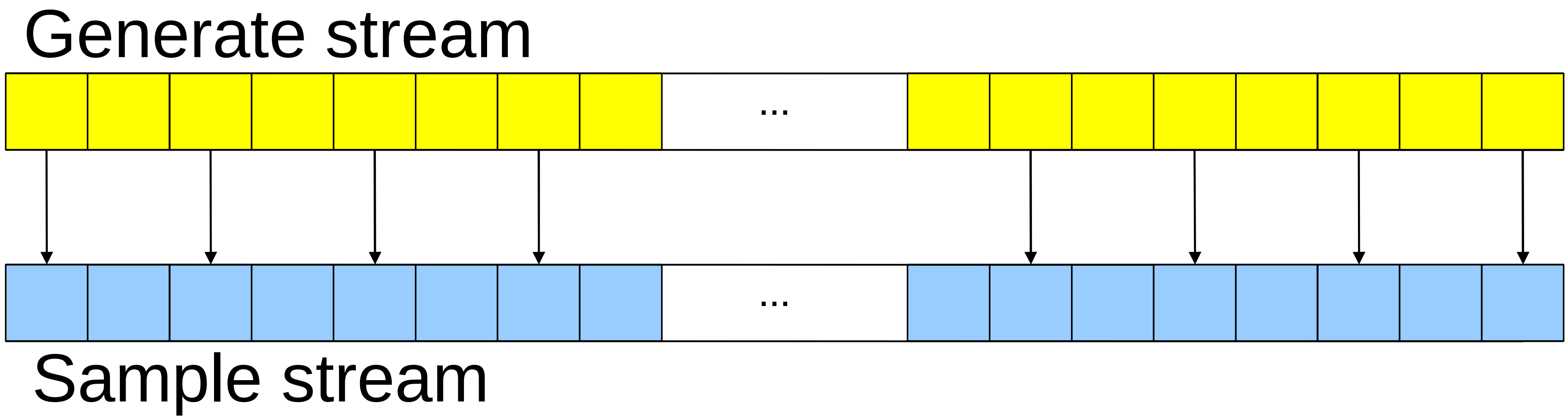
Stream Compaction + Regeneration

- **Remove terminated samples** from the stream using **stream compaction**
- Short stream length may reduce GPU utilization
- **Regenerate terminated samples** at the end of the sample stream

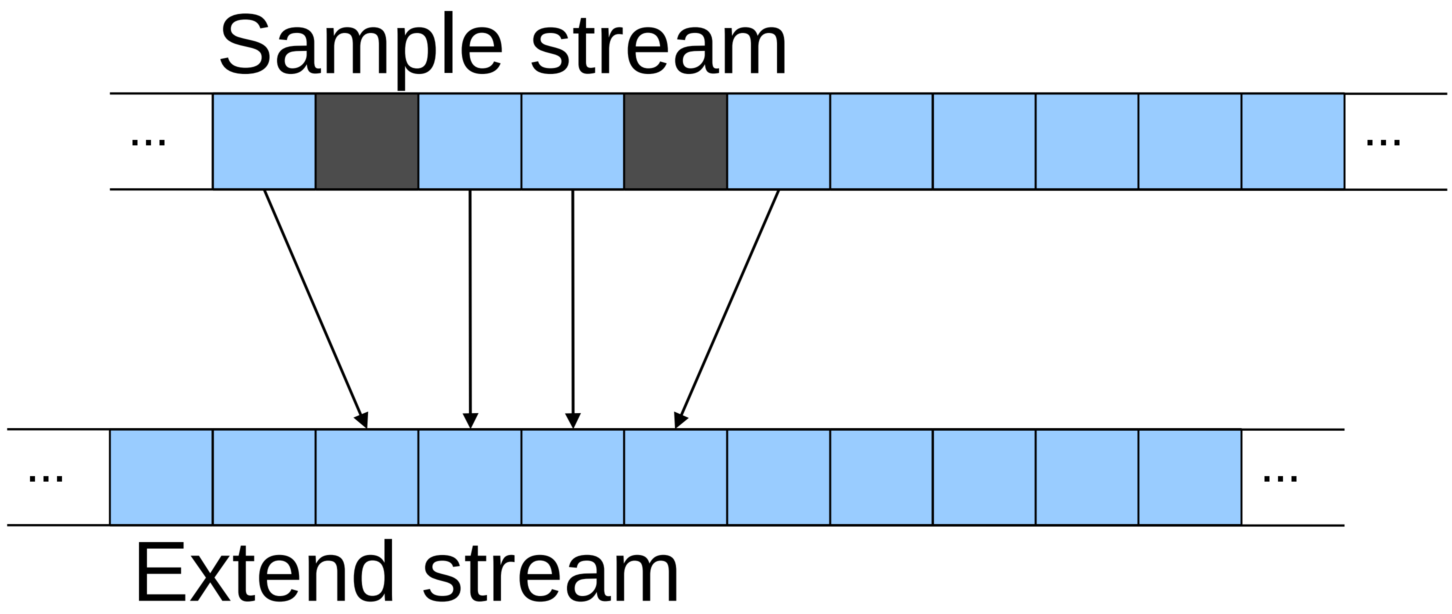
Stream Compaction + Regeneration

- **Initialize** sample stream



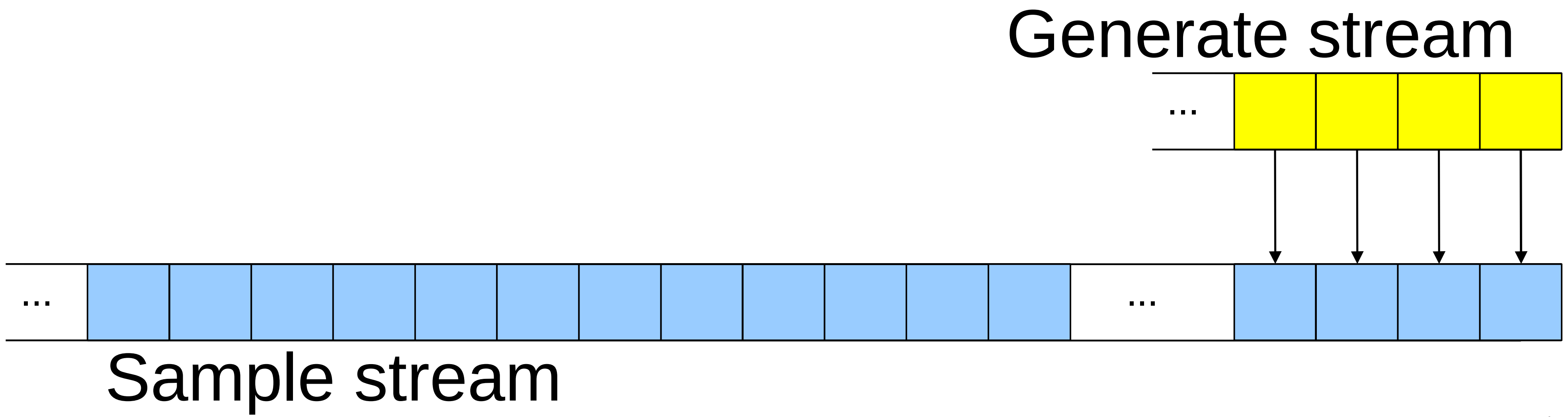
Stream Compaction + Regeneration

- Extend all samples with next path vertex
- Some samples terminate
- **Compact** output **stream**



Stream Compaction + Regeneration

- Output stream becomes next sample stream
- **Regenerate** new **samples** at the end



Advantages

- High SIMD efficiency during extension and connection
- High SIMD efficiency during regeneration
- Fixed size sample stream
- Regenerated samples lie **side-by-side**
- Primary rays benefit from **primary ray coherence**
- **~20% speedup** over in-place sample regeneration

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Bidirectional Path Tracing

- Improve SIMD efficiency during **random walk**
  - Combine stream compaction and regeneration
- Improve SIMD efficiency during **connection**
  - Evaluate all bidirectional connections in parallel

- Algorithm is divided in r*andom walk* and *connect* phase
- Phases execute repeatedly one after the other

Random Walk Phase

- **Initialize** eye and light path stream

Eye path stream

1	2	3	4	5	6	7	8

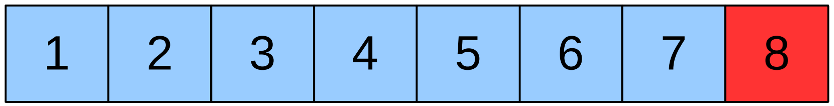
Light path stream

1	2	3	4	5	6	7	8

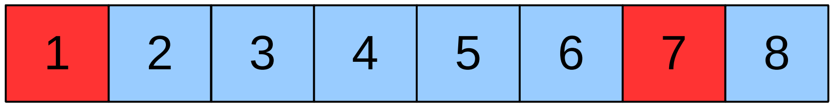
Random Walk Phase

- **Extend** all paths with one vertex
- Some paths terminate

Eye path stream



Light path stream



Random Walk Phase

- **Compact** path streams

Eye path stream

1	2	3	4	5	6	7	8

1	2	3	4	5	6	7

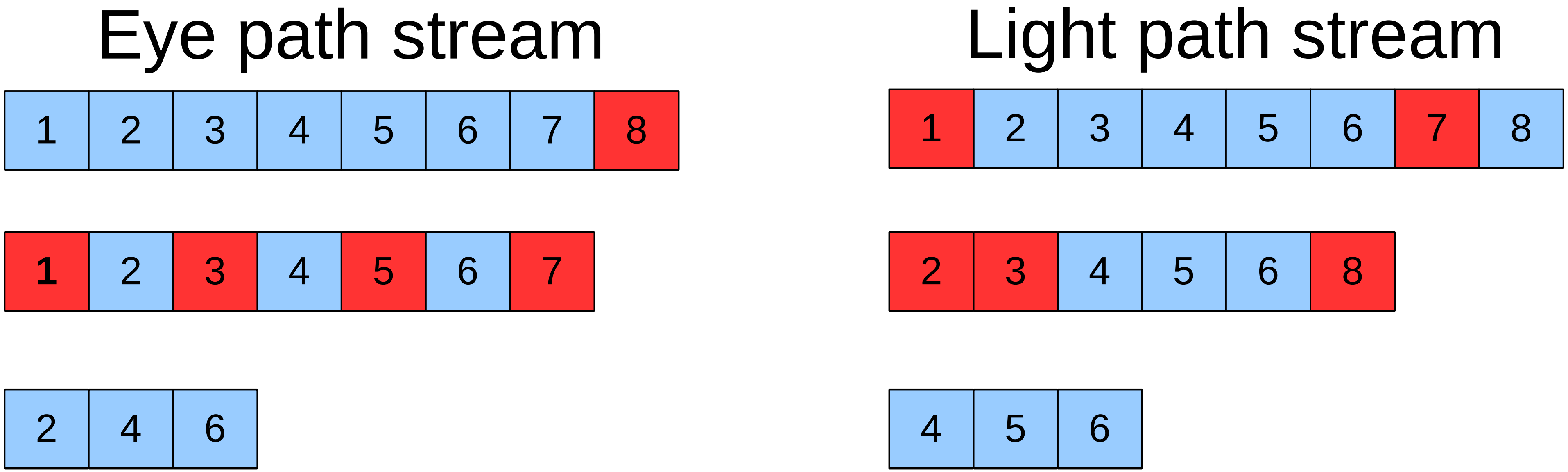
Light path stream

1	2	3	4	5	6	7	8

2	3	4	5	6	8

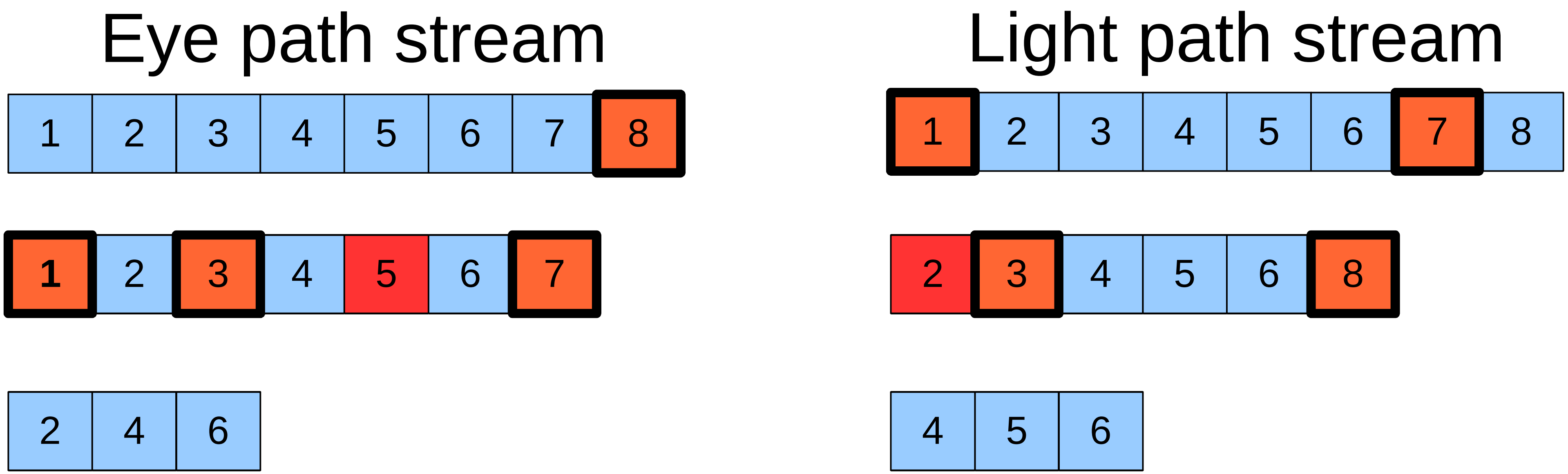
Random Walk Phase

- Repeat extend and compact
- Postpone regeneration



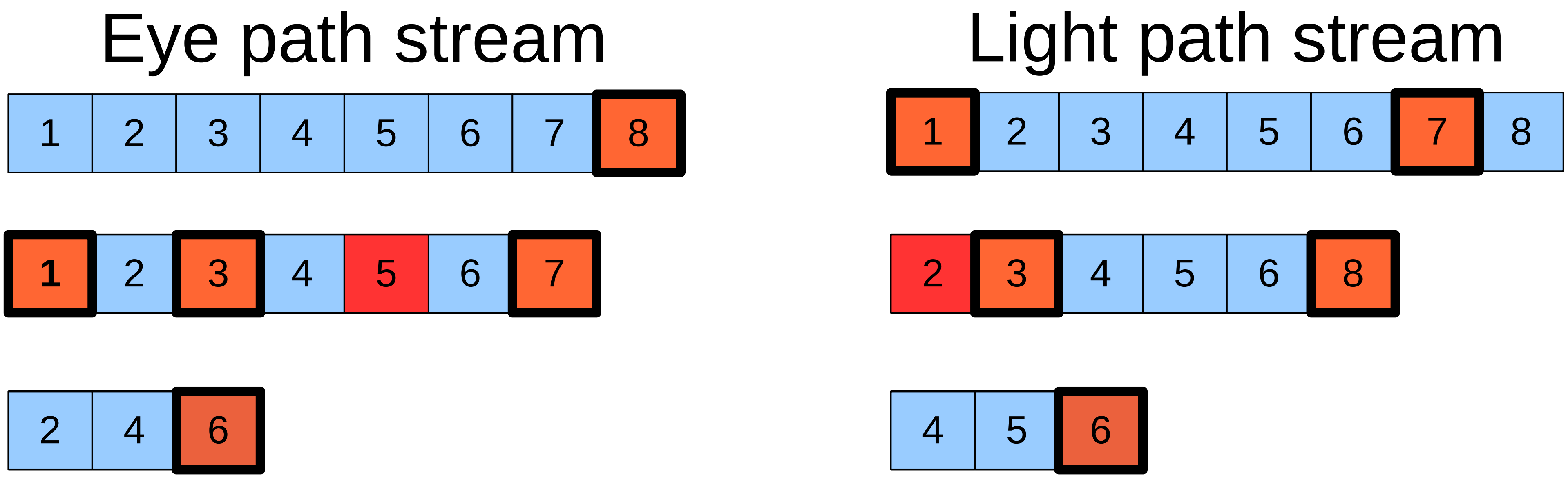
Random Walk Phase

- Sample terminates when **both** eye and light path have terminated



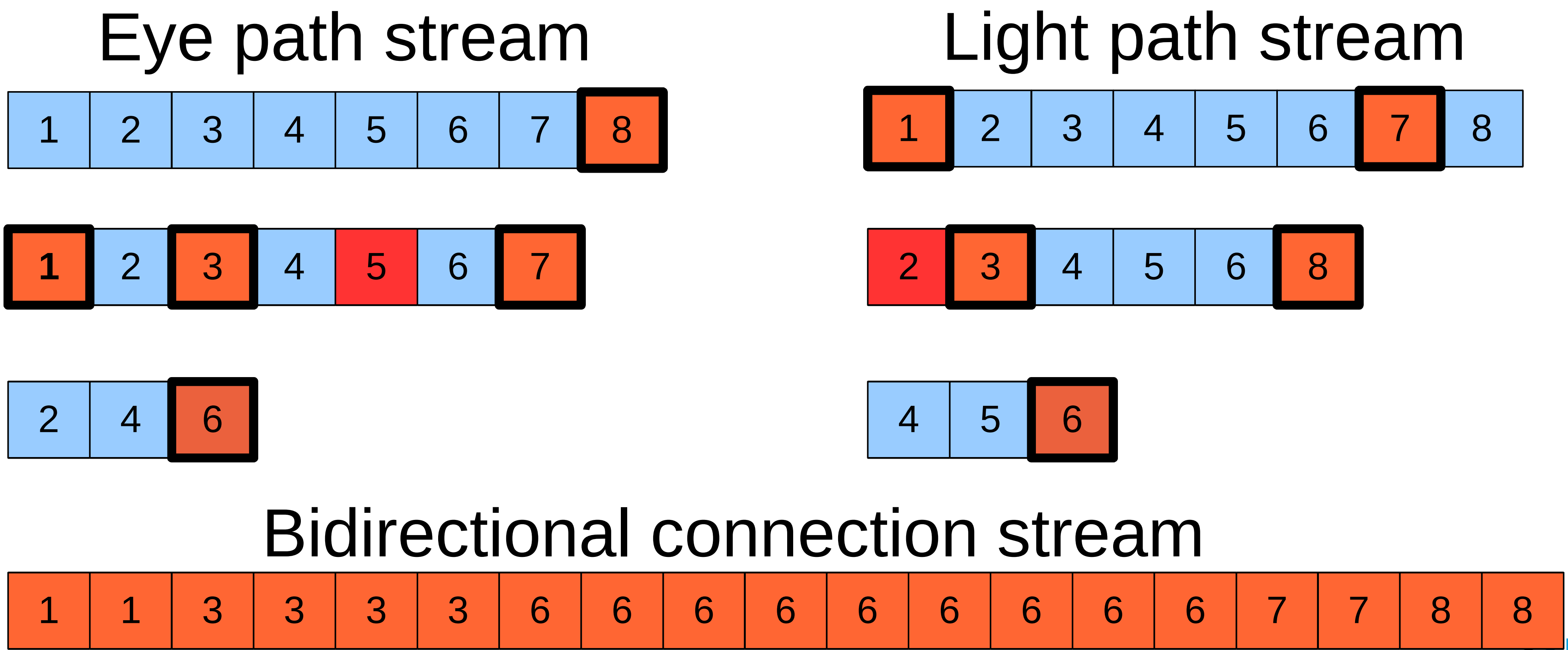
Random Walk Phase

- Repeat until **60%** of samples terminated



Bidirectional Connect Phase

- Evaluate connections for **terminated** samples
- Generate stream of bidirectional connections

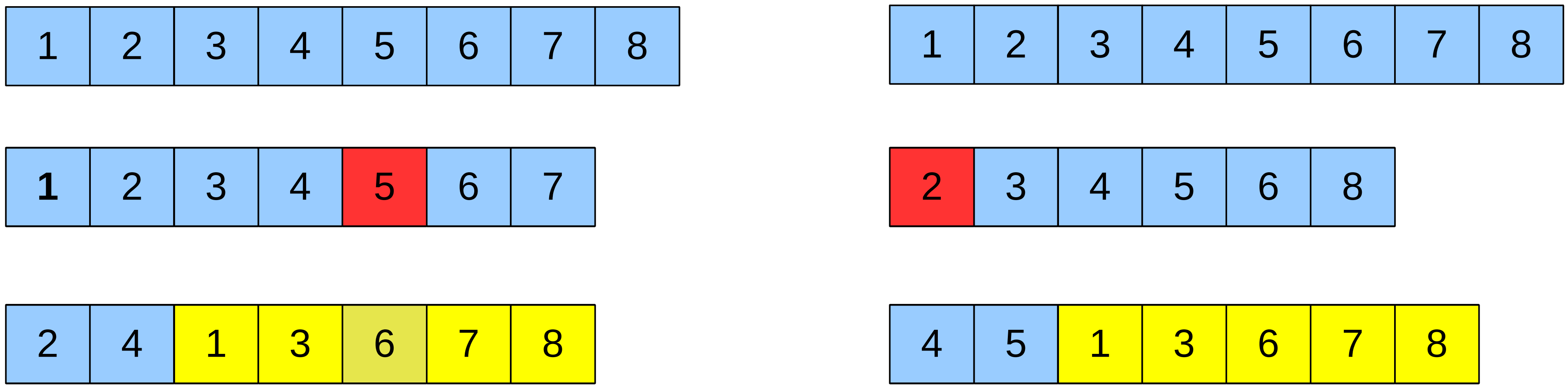


Sample Regeneration

- **Regenerate** terminated samples and resume random walk phase

Eye path stream

Light path stream



Sample Regeneration

- Sample regeneration keeps path streams long
- Good for GPU utilization
- Total **speedup ~15%**
- Less than for path tracing
- Sample regeneration only improves random walk phase
- BDPT spends only **~55% in random walk** phase

Bidirectional Connect Phase

- Evaluate all connection **in parallel**
- Each terminated sample contributes #connections
- Execute thread for each connection
- Threads **figure out** which connection to evaluate using
  - Parallel scan over all samples
  - Binary search for each connection thread
- See paper for details...

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Metropolis Light Transport

- Run many **independent** MLT **samplers** in **parallel**
- Based on the BDPT implementation
- Use variation on Kelemen mutation
- Only mutate sample dimensions used in both current and mutated sample
- Estimate normalization constant on the fly

Startup Bias

- Each MLT sampler introduces startup bias
- Many parallel samplers means **lots of bias**
- Bias is usually larger for difficult scenes

10 seconds

Reference

Startup Bias

- Each MLT sampler introduces startup bias
- Many parallel samplers means **lots of bias**
- Bias is usually larger for difficult scenes

1 minute

Reference

Startup Bias

- Each MLT sampler introduces startup bias
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- Bias is usually larger for difficult scenes

10 minutes

Reference

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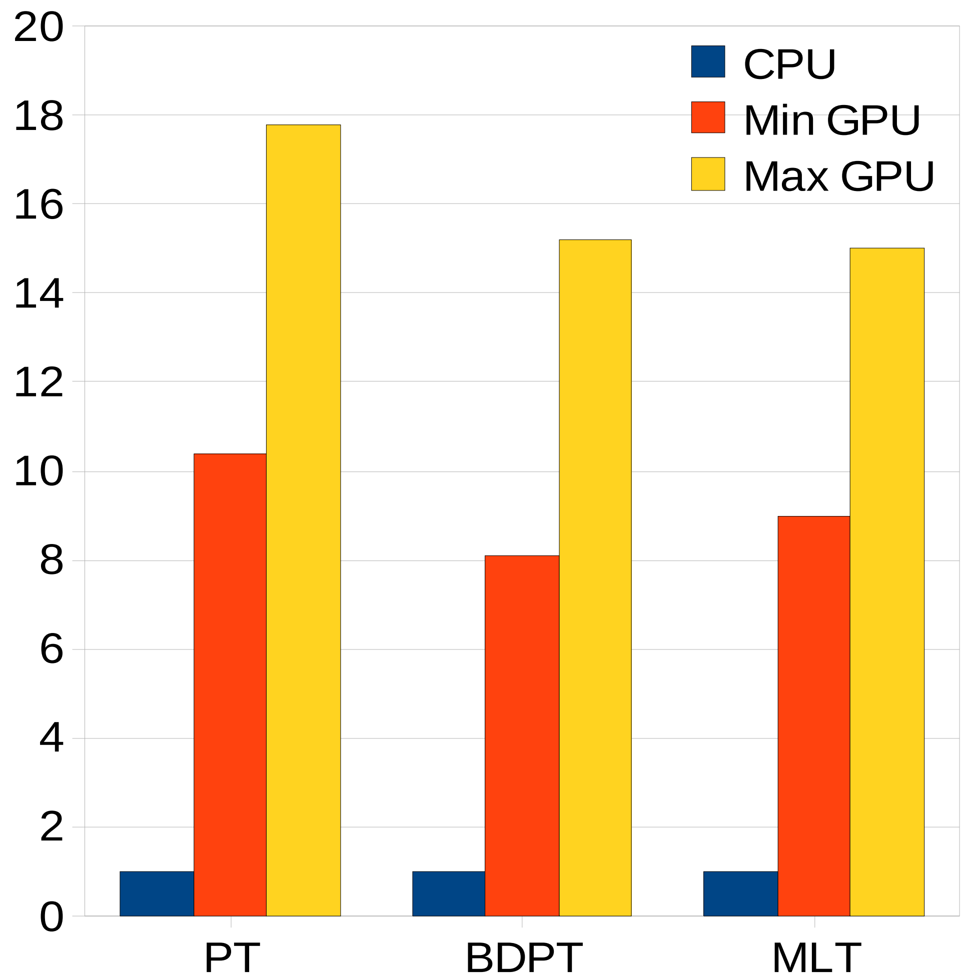
SIMD efficiency

- Algorithms always work on **continuous streams**
- Active threads per GPU warp **~99%**
- **Upper bound** on actual SIMD efficiency
- Actual SIMD efficiency lower due to divergent shader/traversal code
- Performance improvement less than SIMD efficiency improvement...

GPU vs. CPU

- Compared with straightforward multicore CPU implementation
- NVIDIA GTX 480 GPU
- Intel Core i7 920 CPU
- Speedup **between 8x and 15x**
- *GPU can do more than path tracing!*



Speedup

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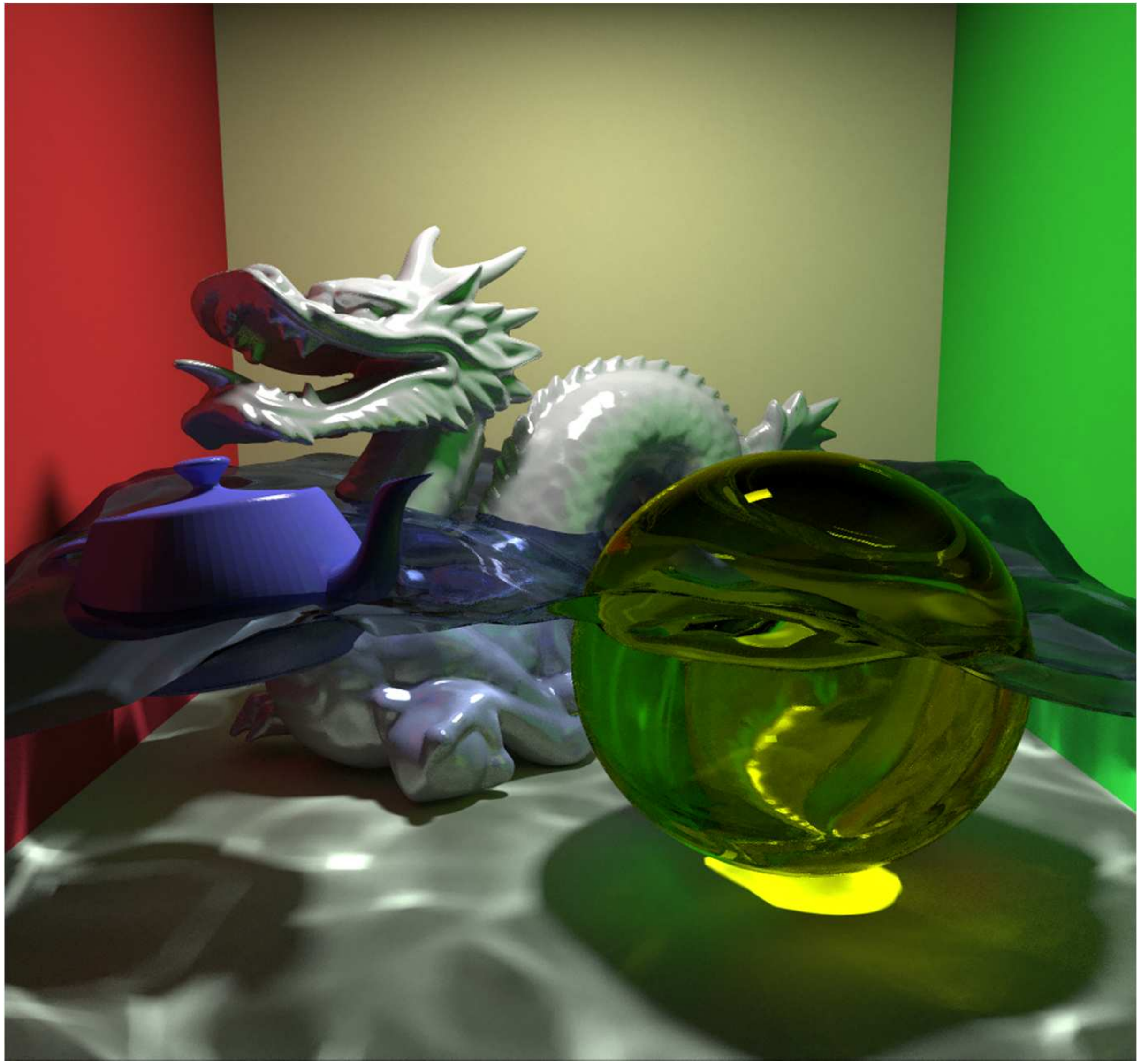
Demo



Questions?

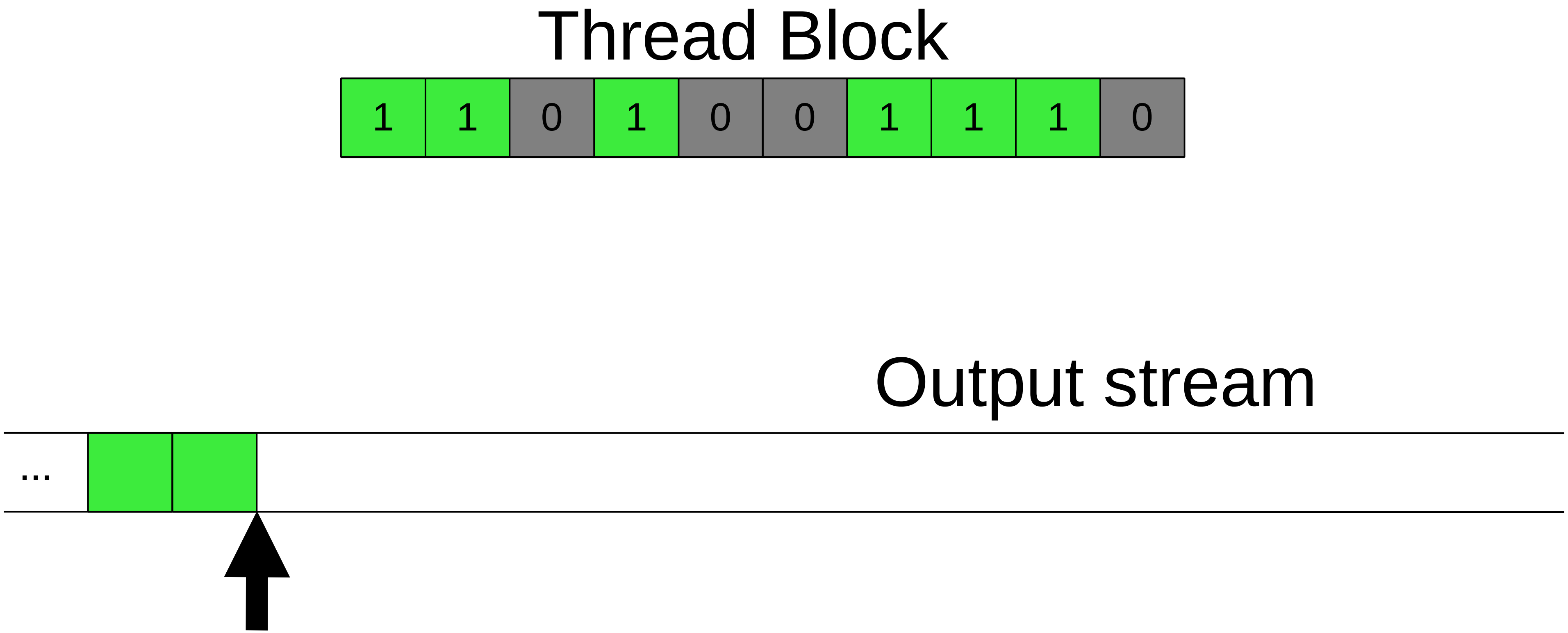
Extra

Immediate Stream Compaction

- Stream compaction requires **multi-pass** parallel scan and scatter pass
- Immediate stream compaction in **single pass**
- **Parallel scan** per block in shard memory
- Block **allocates** space in output buffer using one **atomic add**
- Threads write items **directly** into compacted output stream

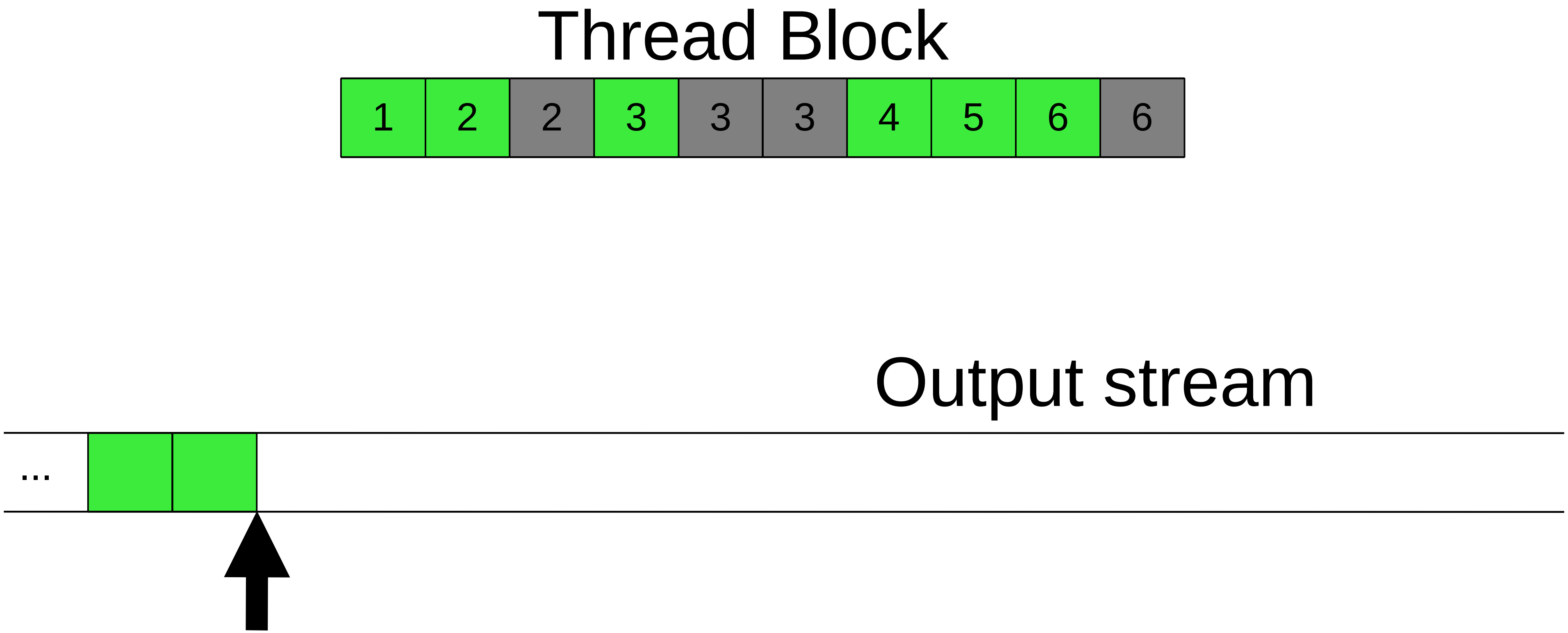
Immediate Stream Compaction

- **Label** all active threads



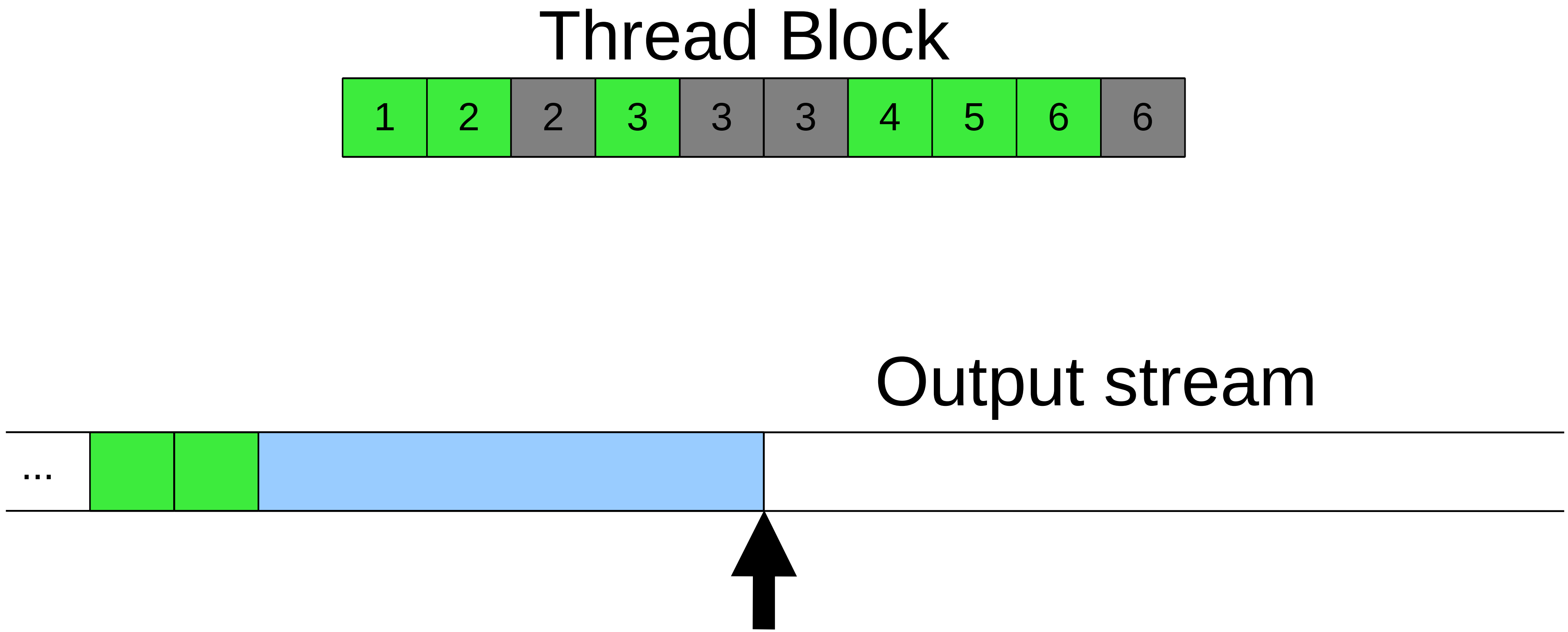
Immediate Stream Compaction

- **Parallel scan** per block in shared memory



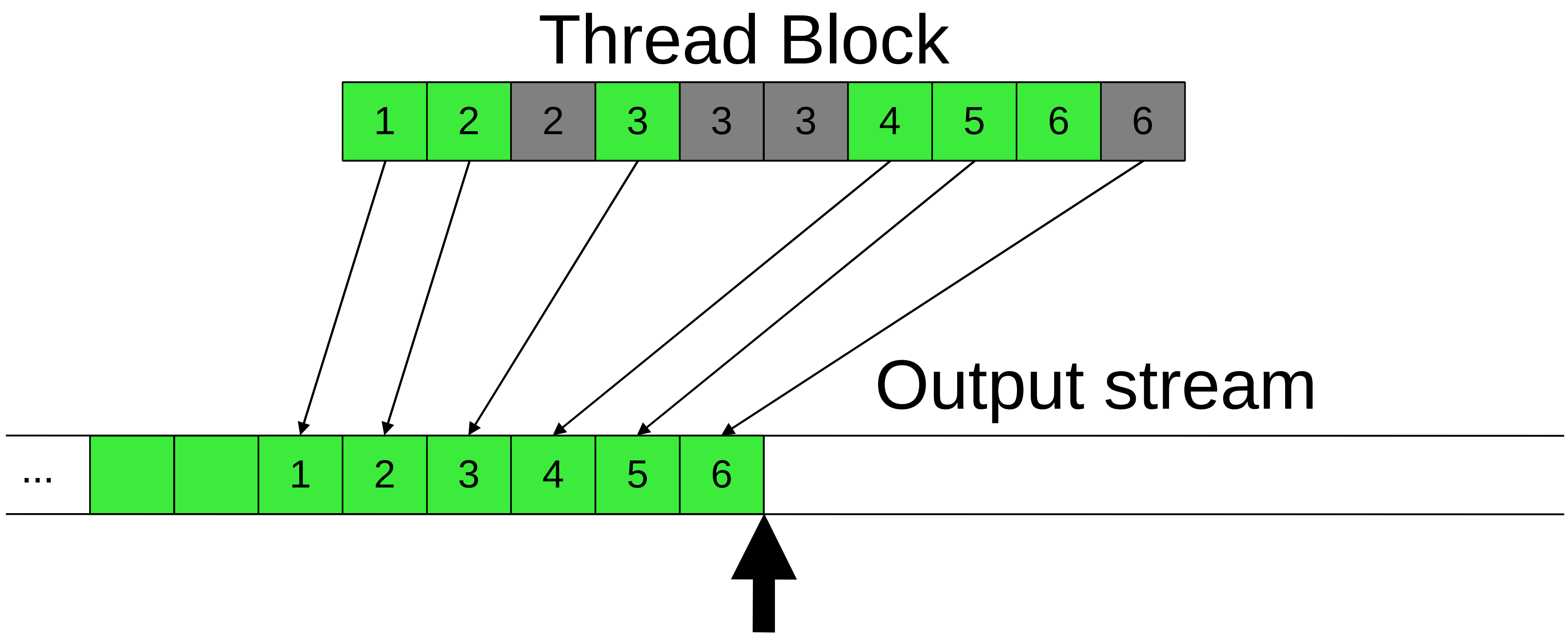
Immediate Stream Compaction

- Block **allocates** memory in output stream using an **atomic instruction**



Immediate Stream Compaction

- Each active thread **writes** directly in the **output stream**



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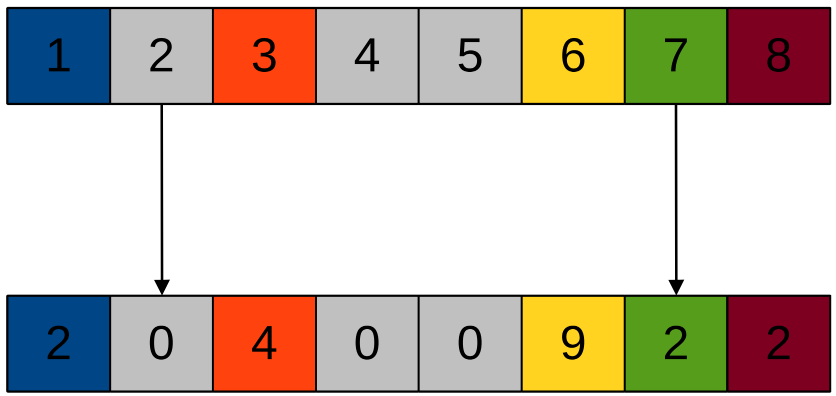
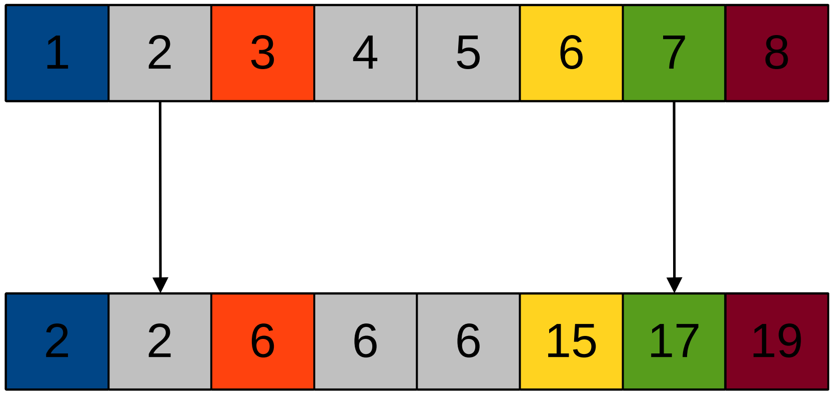
Parallel Bidirectional Connect

- Each sample **writes #connections** in connection count buffer
- Non-terminated samples write a zero



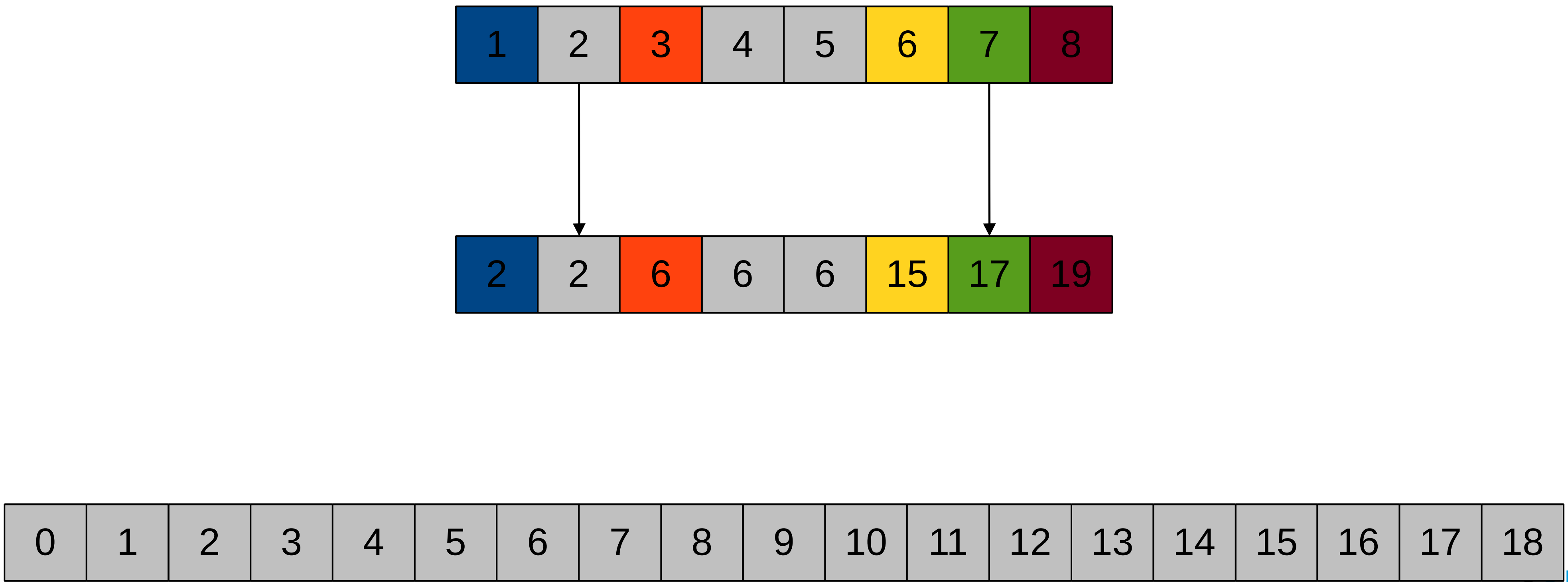
Parallel Bidirectional Connect

- **Parallel scan** the connection count buffer
- Gives the #connections preceding each sample in the buffer



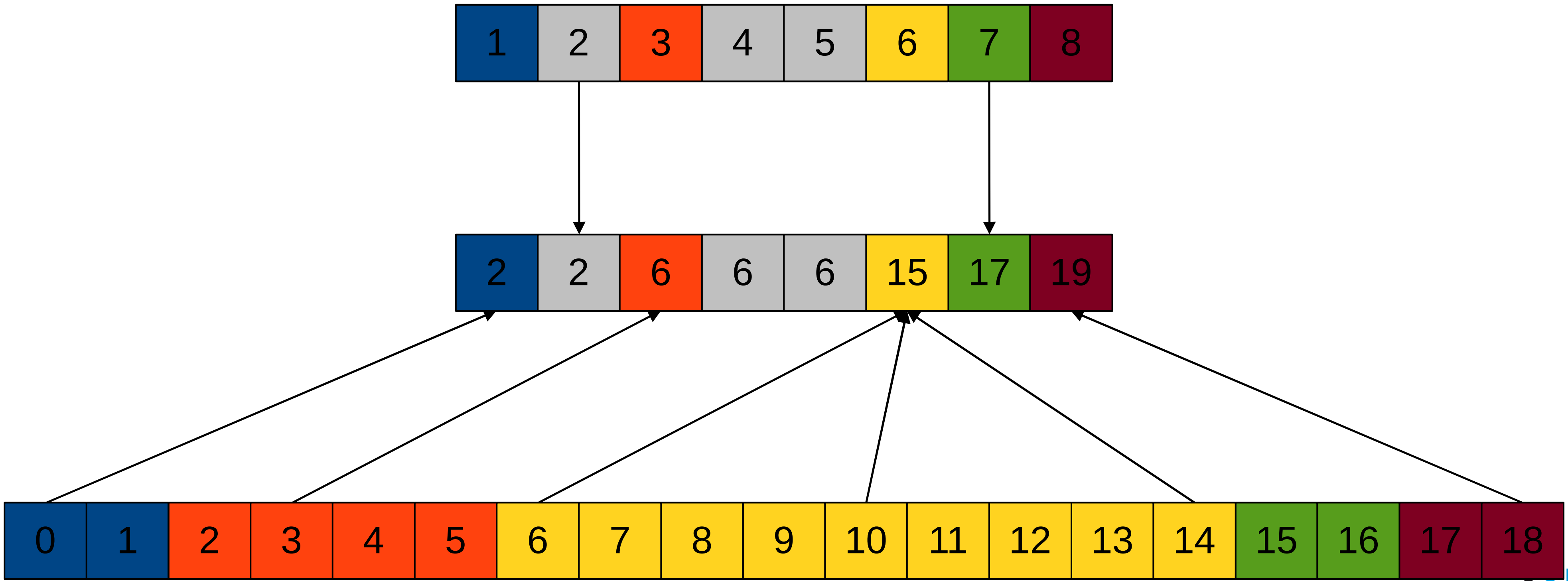
Parallel Bidirectional Connect

- Start one GPU thread for **each** connection



Parallel Bidirectional Connect

- **Binary search** thread index for corresponding sample in connection count buffer



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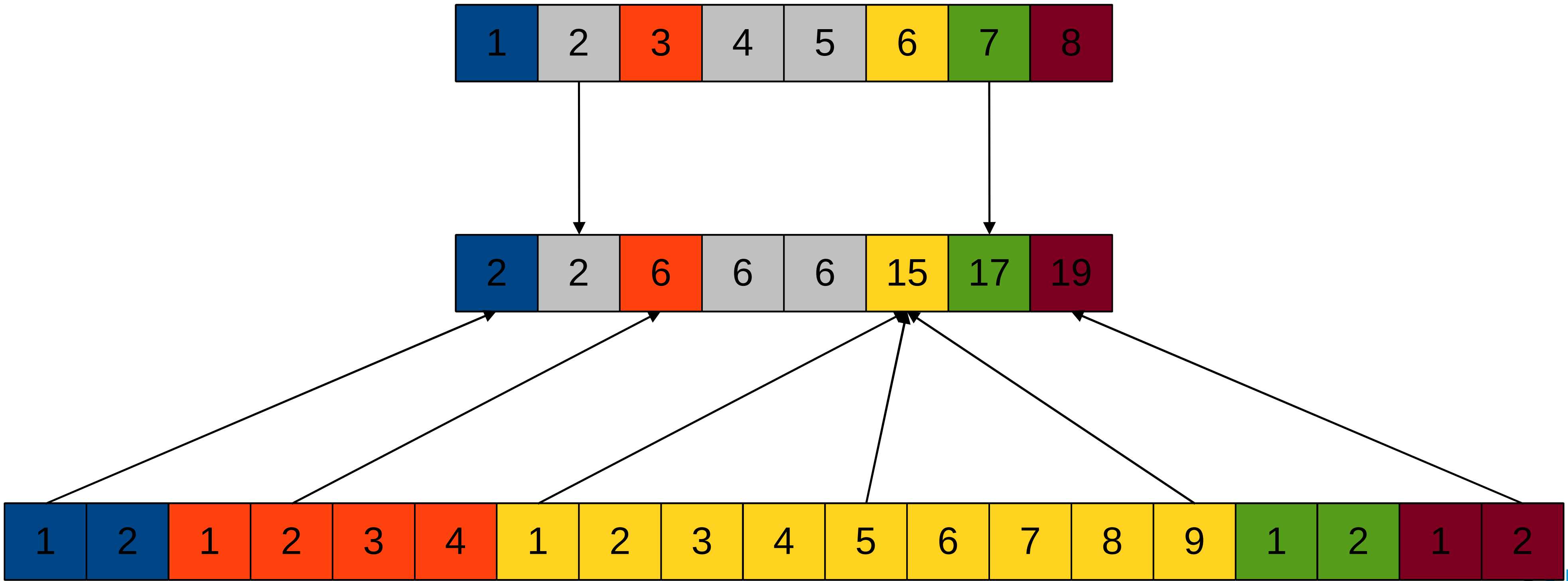
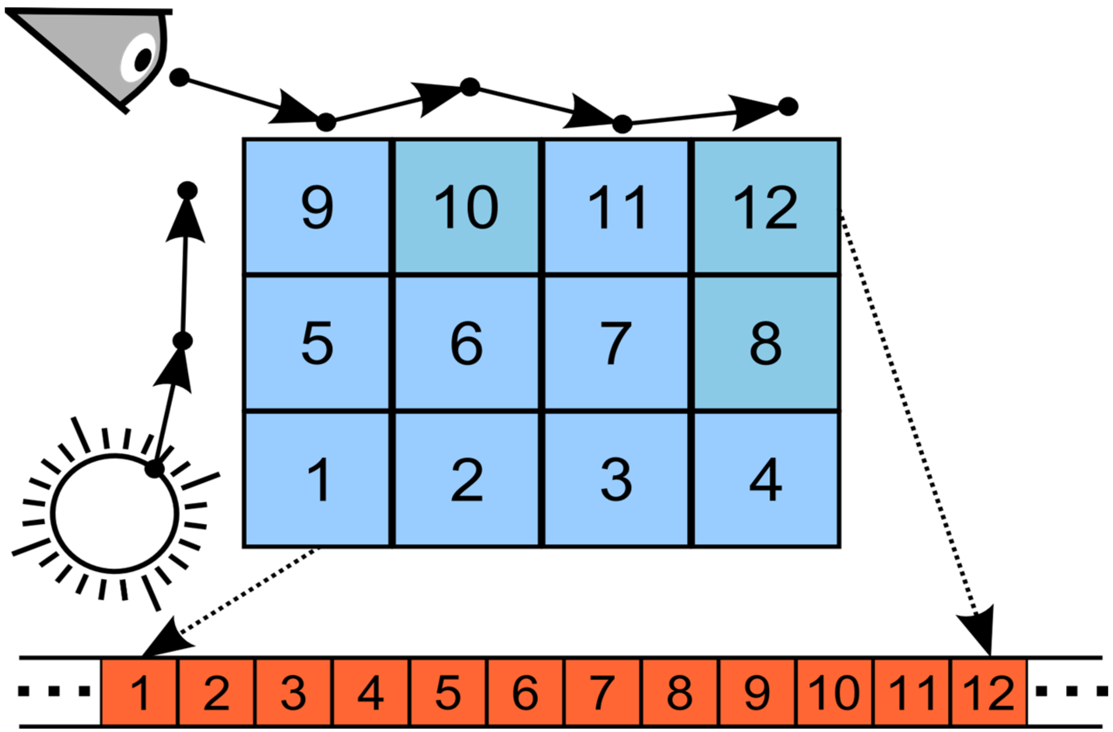
Parallel Bidirectional Connect

- Compute **local connection index** from sample connection count



Parallel Bidirectional Connect

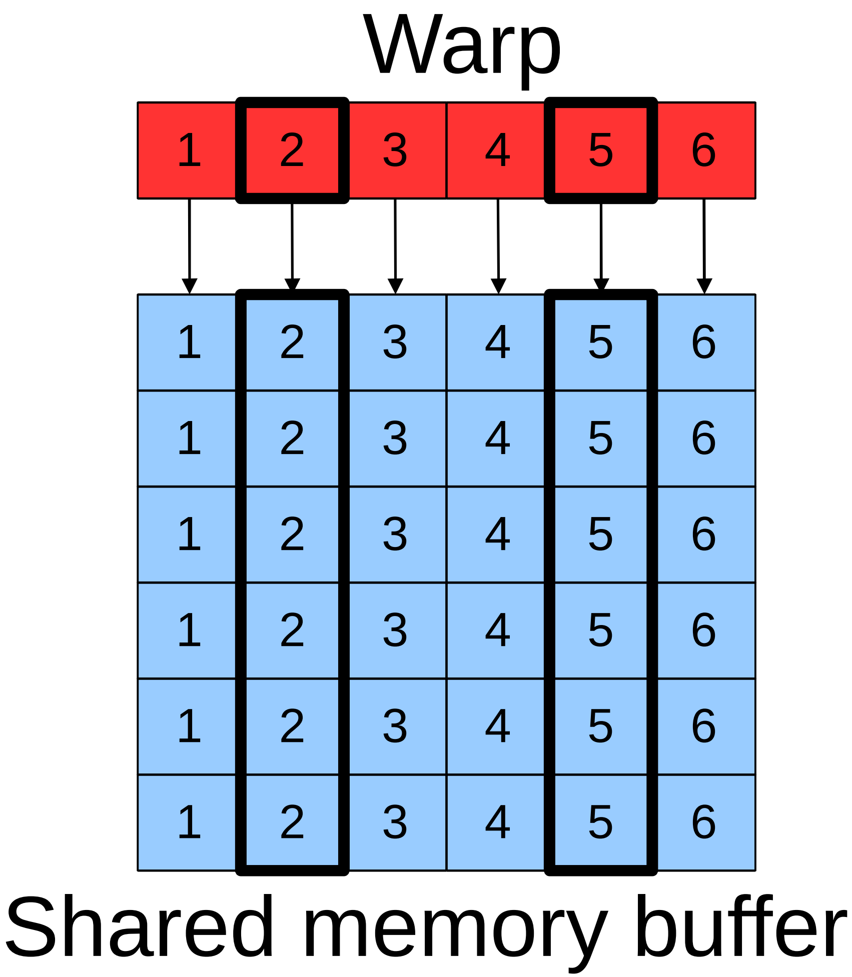
- Local connection indices **map to** an **eye-light vertex pair** to connection
- Each thread evaluates its connection



Coalesced Vertex Scattering

- Path vertices are stored during random walk
- Vertices are scattered to pre-allocated vertex memory
- Each thread scattering its vertex would result in uncoalesced memory access
- **Threads** in a warp **collaborate** to **efficiently scatter** path **vertices** to memory
- Vertices are scattered through shared memory
- Similar to matrix transpose

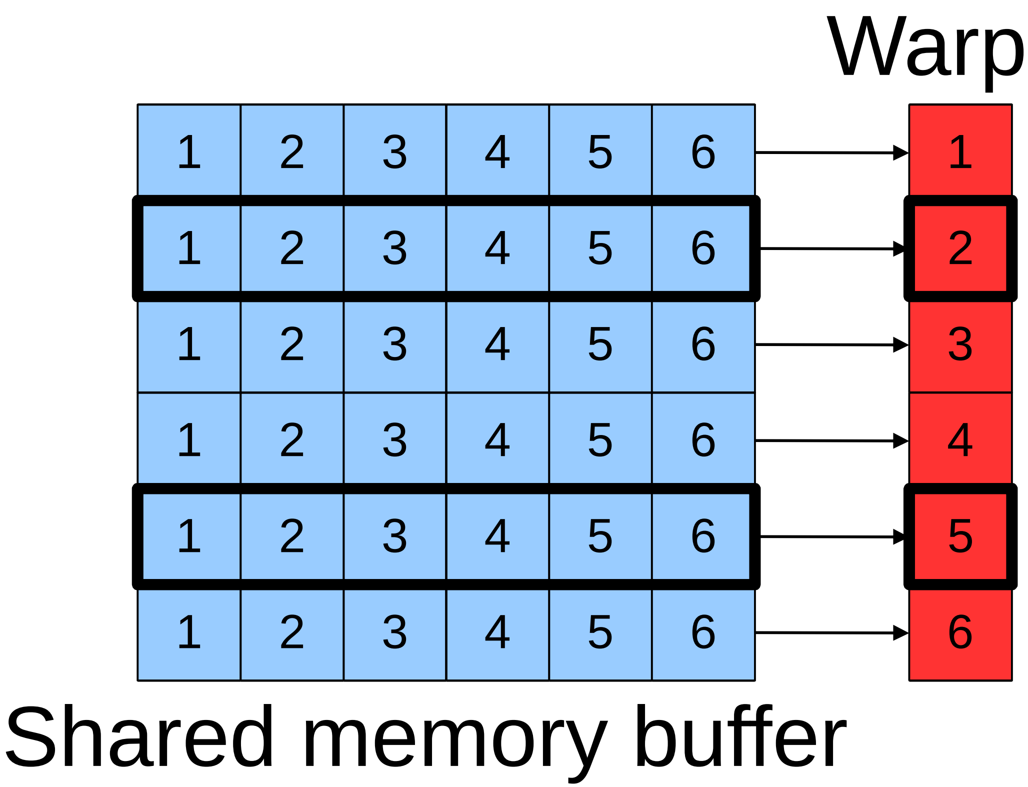
Coalesced Vertex Scatter



- Vertex is 128 bytes
- Each thread in warp writes vertex to shared memory

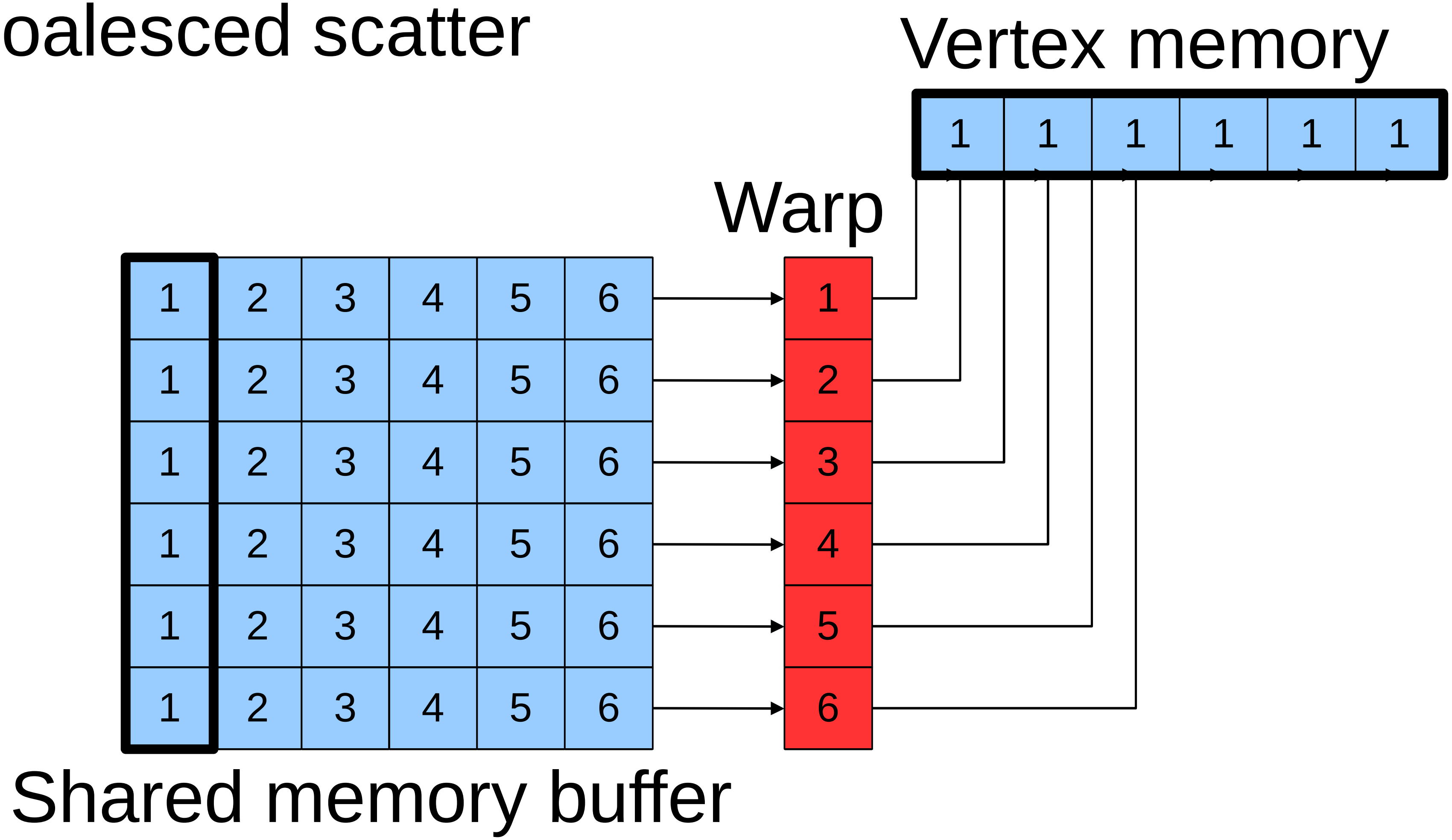
Coalesced Vertex Scatter

- Each thread in warp reads one word from each vertex in shared memory buffer



Coalesced Vertex Scatter

- Each thread scatters one word of each vertex
- Coalesced scatter



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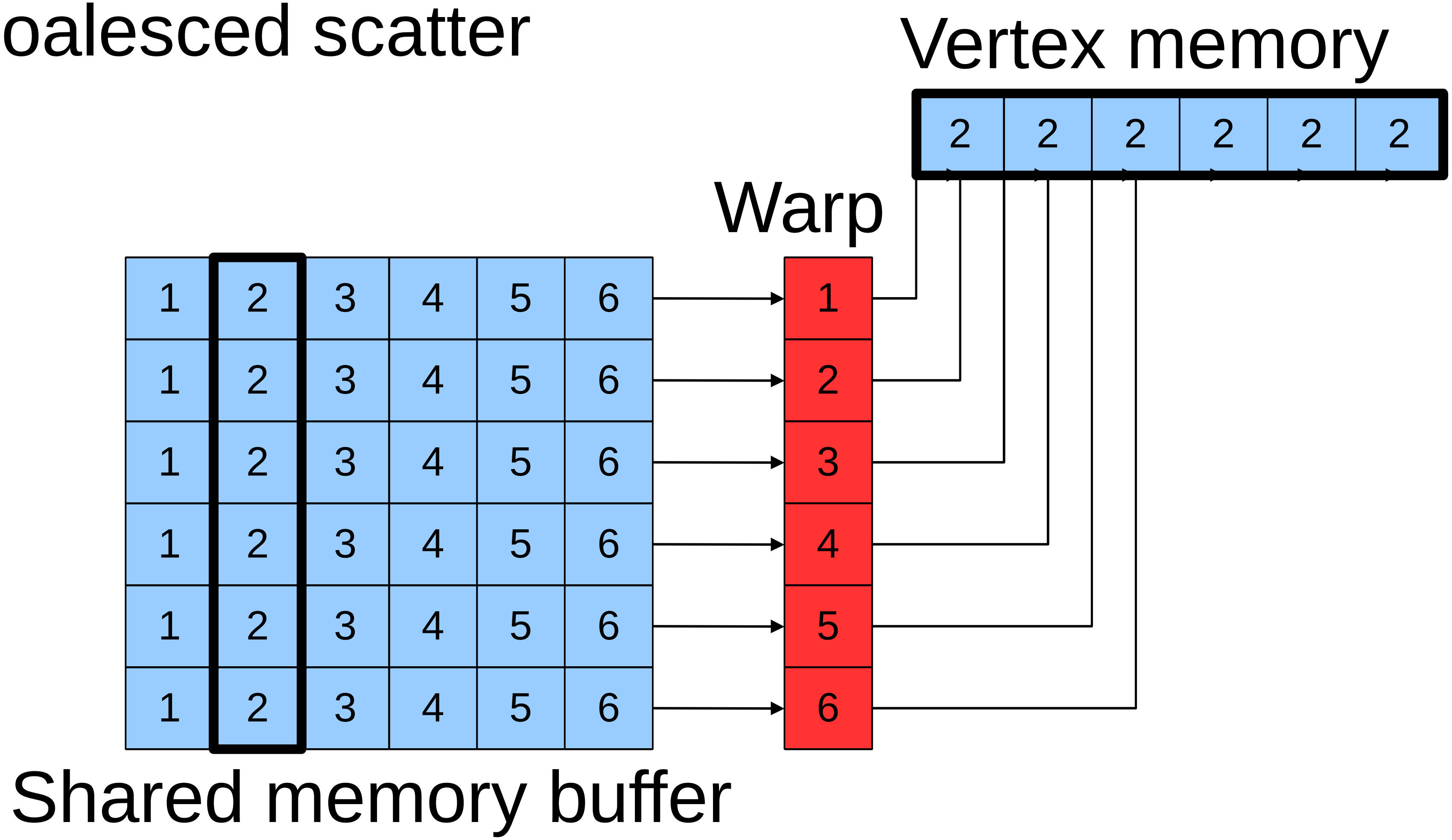

Coalesced Vertex Scatter

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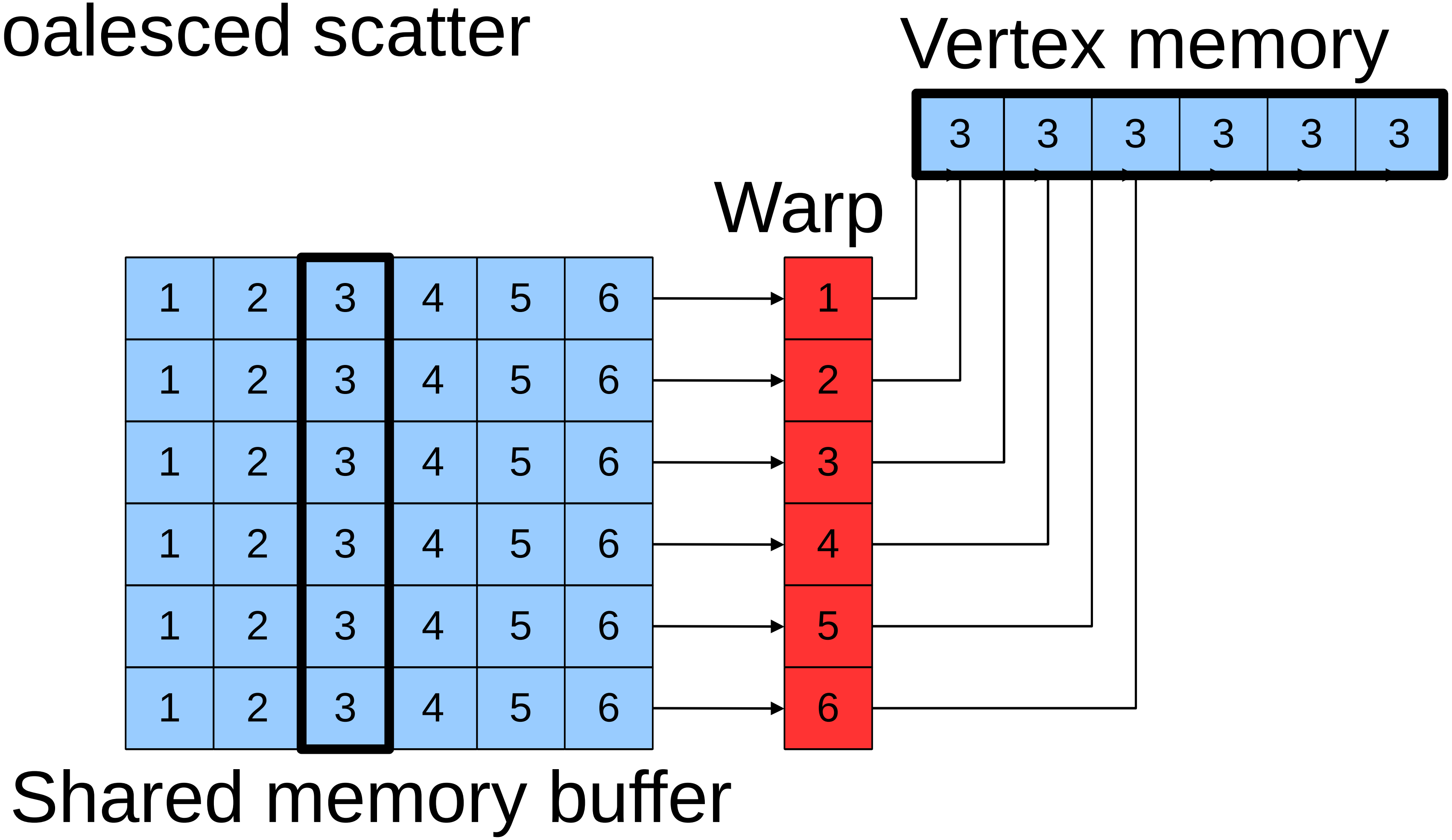

Mutation Strategy

- Kelemen et al. proposed to lazily perturb all infinite dimensions
- Leads to uneven workload during mutation
- Instead, perturb **only dimensions** used in **both** the **current** and **mutated** sample
- Regenerate other dimensions
- Keeps the strategy symmetric
- Reduces memory usage
- Even workload per path vertex