



Tiling-Based Programming Model for Structured Grids on GPU Clusters

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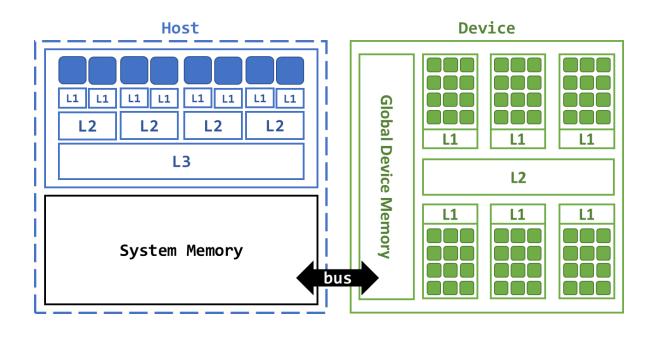
Outline

- **Motivation**
- Overview
- Implementation
- Performance
- Related Work
- Future Work

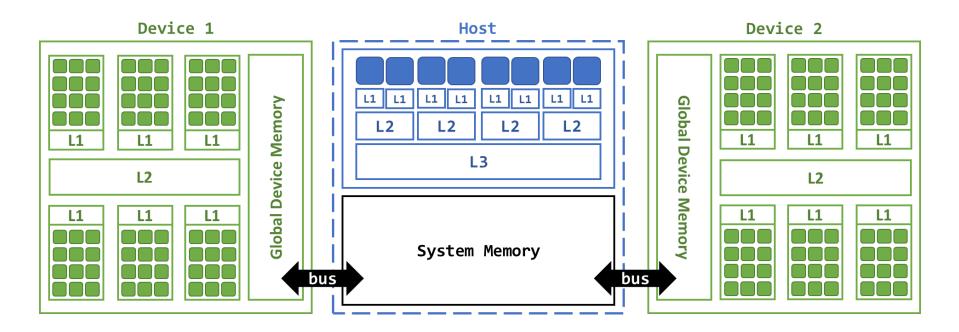
- Moore's Law is no longer applicable
- GPUs have massively parallel and power-efficient architectures that accelerate data-parallel applications
- As a result GPU-based heterogenous systems became popular
 - They constitute more than 25% of supercomputers on TOP500 list
 - The percentage keeps increasing



- Programming a single-GPU system is a demanding task because it requires
 - Managing distinct address spaces
 - Implementing GPU-specific code (kernels)

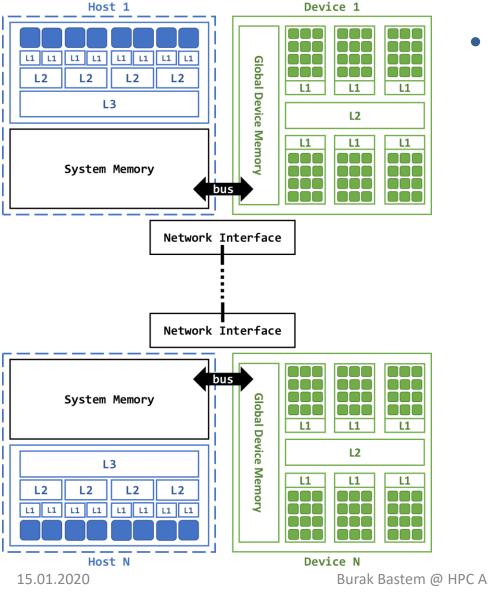






- Having multiple GPUs on a host
 - Complicates address space management
 - Additionally requires distributing the work



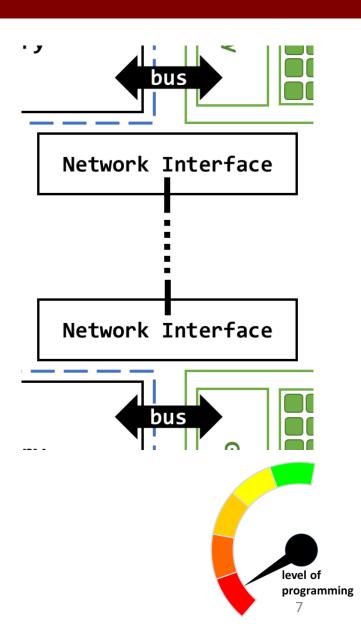


- Programming a GPU cluster is even more demanding since it additionally requires
 - handling communication between host



Burak Bastem @ HPC Asia 2020

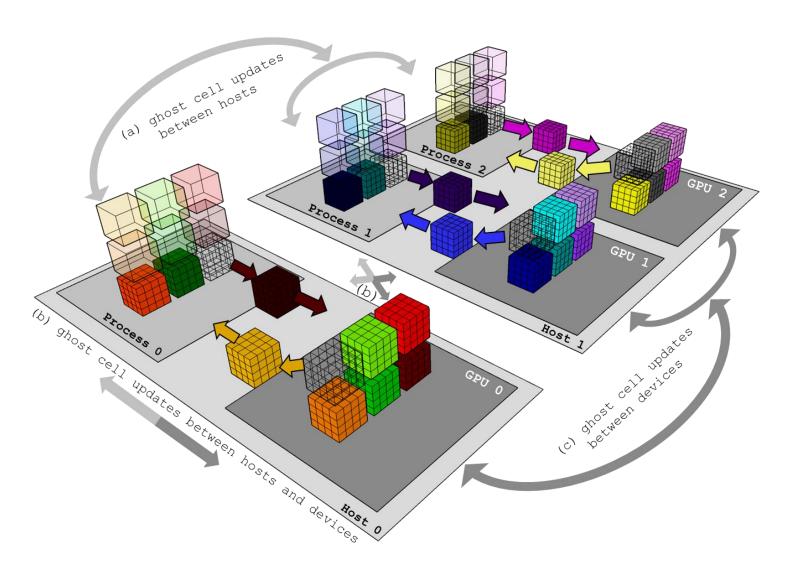
- The interconnect linking GPUs to host has a lower bandwidth than host and device have
 - Transfers between hosts and devices need to be optimized
- Communication across cluster needs to be optimized for better scalability



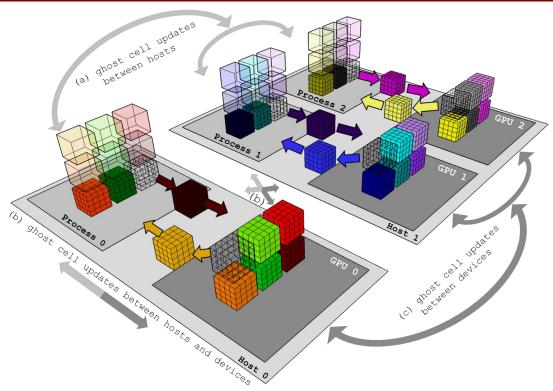
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Tiling-Based Programming Model

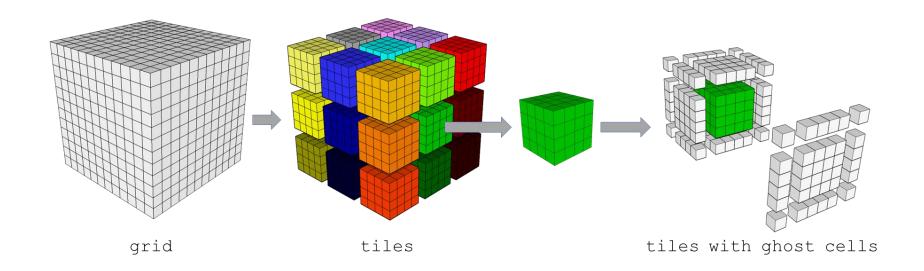


Tiling-Based Programming Model



- Manages distinct address spaces itself
- Automatically generates kernels
- Handles transfers between hosts and devices and communication across cluster
 - Also overlaps them with computation
 - Provides a solution for the interconnect bandwidth limit

Fundamental Data Structures



- Programming with Tiling Data Abstractions (TiDA)
 - Tile: Data partition
 - Tile Array: Responsible for partitioning, memory management, ghost-cell update
 - Tile Iterator: Iterates over tiles on CPUs and/or GPUs

```
TileArray ta(app_data, data_dim, tile_dim, ghost_cell_dim);
2 for(TileArray::Iterator i = ta.begin(gpu_exec_ratio); i != ta.end(); ++i) {
3   Tile t = *i;
4   compute(t, [](double* data,int depth,int height,int width,int index){
5    data[index] = ...//computation
6   });
7 }
8 ta.updateGhostCells();
```

```
1 TileArray ta(app_data, data_dim, tile_dim, ghost_cell_dim);
2 for(TileArray::Iterator i = ta.begin(gpu_exec_ratio); i != ta.end(); ++i) {
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```

Line 1 creates a tile array

```
1 TileArray ta(app_data, data_dim, tile_dim, ghost_cell_dim);
2 for(TileArray::Iterator i = ta.begin(gpu_exec_ratio); i != ta.end(); ++i) {
3   Tile t = *i;
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8 ta.updateGhostCells();
```

- Line 2 starts an iteration with for-loop
 - Syntax is the same as the syntax of iterating through a standard C++ list
- gpu_exec_ratio specifies the fraction of tiles that will be executed on GPUs

```
TileArray ta(app_data, data_dim, tile_dim, ghost_cell_dim);
2 for(TileArray::Iterator i = ta.begin(gpu_exec_ratio); i != ta.end(); ++i) {
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8 ta.updateGhostCells();
```

Line 3 gets a tile by dereferencing the iterator

```
TileArray ta(app_data, data_dim, tile_dim, ghost_cell_dim);
2 for(TileArray::Iterator i = ta.begin(gpu_exec_ratio); i != ta.end(); ++i) {
3   Tile t = *i;
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5    data[index] = ...//computation
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7 }
8 ta.updateGhostCells();
```

- compute is a function which takes the tile and a lambda expression
 - Lambda contains the computation and hides kernel code generation

```
TileArray ta(app_data, data_dim, tile_dim, ghost_cell_dim);
2 for(TileArray::Iterator i = ta.begin(gpu_exec_ratio); i != ta.end(); ++i) {
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8 ta.updateGhostCells();
```

Line 8 updates ghost cells

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Implementaion

- Implemented as a library
 - https://bitbucket.org/parcorelab/gpu-cluster-tilingprogramming-model.git
- Uses multiple processes
 - Each process gets a GPU
- Partitions data into tiles with TiDA
- Manages memories with CUDA
- Leverages OpenACC for kernel generation
 - Hides directives with lambda expression
- Exploits CUDA streams for asynchronous GPU operations
- Uses non-blocking MPI routines to hide communication behind computation

Memory Management

Three different memory options:

Pageable

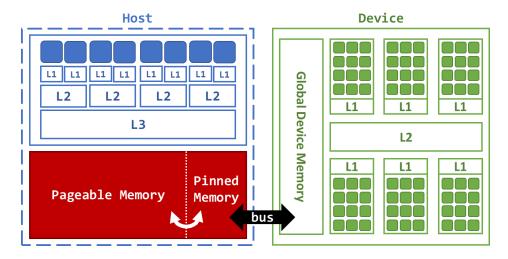
- During a memory transfer between host and device, pageable memory implicitly copied from/to pinned memory
- Default memory allocations are pageable

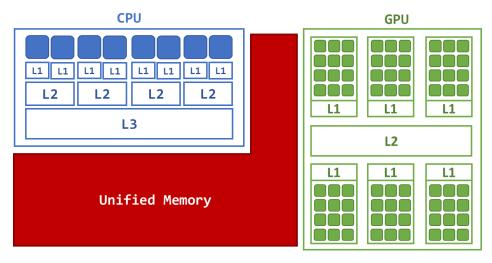
Pinned

Programmer can directly allocate pinned memory

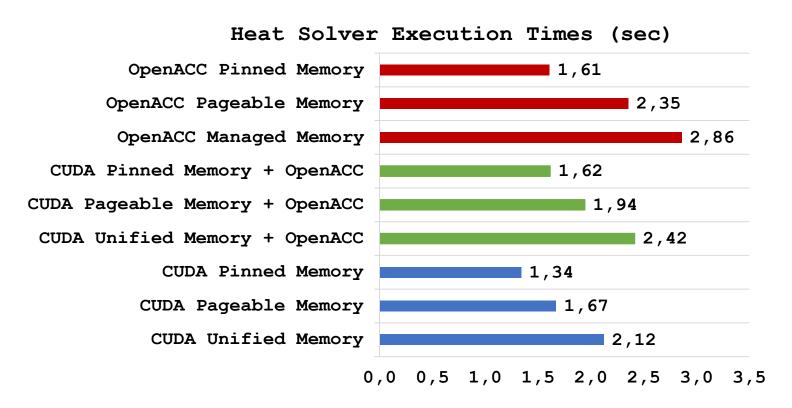
Unified

 Host and device memory appears a single memory





Performance of Memory Types



- GPU: NVIDIA K40
- CUDA + OpenACC versions use CUDA for memory management and OpenACC for kernel generation
- ✓ The library uses CUDA pinned memory for memory management

Kernel Generation

Using CUDA

- Forces programmer to implement kernels
- Or requires in-house compiler implementation which needs support for longevity

✓ Using OpenACC

- Directives are easy to use
- Directives can be hidden in library
- Supported and maintained by NVIDIA

Overlapping Memory Transfers

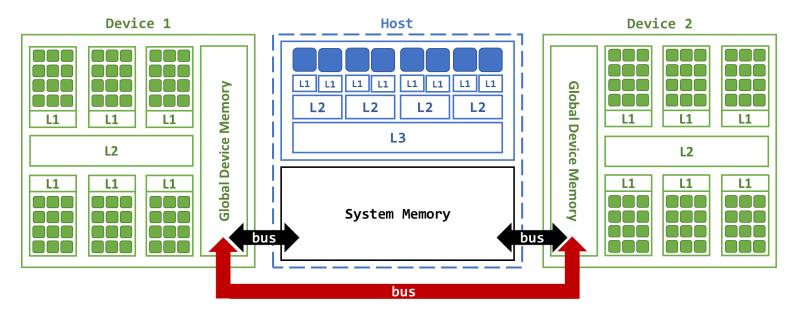
- Employs CUDA streams to overlap device operations
 - Stream is a sequence of device operations
 - GPUs can execute different streams concurrently
- Assigns a CUDA stream to each tile
 - Operations of a tile overlaps with operations of other tiles
 - In case a GPU has limited memory, some tiles share streams
 - Overlapping prevents performance penalty

s1:	D2H: R1 H2D: R3	C: R3	D2H: R3 H2D: R5	
s2:	C: R2	D2H: R2 H2D: R4	C: R4	

- Avoids unnecessary memory transfers with
 - Cache mechanism
 - Lazy initialization

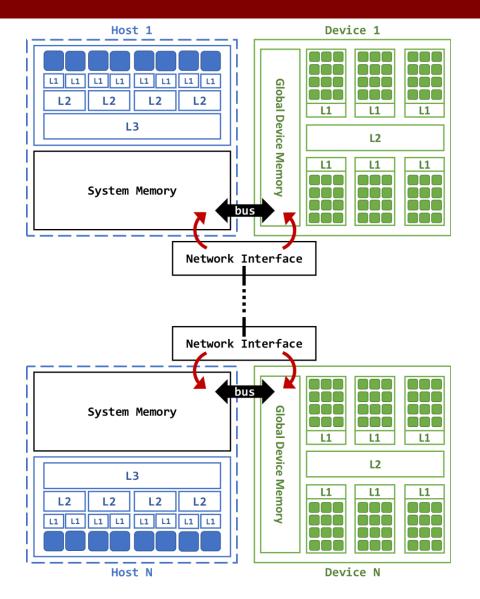
Communication

- Utilizes non-blocking MPI routines
- Employs packing-unpacking for ghost cells
- Supports GPUDirect with CUDA-aware MPI
 - GPUDirect Peer-to-Peer (P2P) Transfer



Communication

- Supports GPUDirect with CUDA-aware MPI
 - GPUDirect RemoteDirect MemoryAccess (RDMA)



Communication

- Phase I: push stream events to each stream of region
- Phase II: pack and send
 - Initiate non-blocking MPI receives
 - Pack ghost cells to buffers (initiate the ones on the device)*
 - Send the ones on the host with non-blocking MPI send
- Phase III: send
 - Sync packing of ghost cells on the device
 - Send them with non-blocking MPI send
- Phase IV: transfer
 - Initiate packing ghost cells on the device that needs to be sent to the host
 - Initiate transfer of these buffers
 - Push transfer event to their stream
 - Pack ghost cells on the host that needs to be sent to the device
 - Initiate transfer of these buffers
- Phase V: exchange cells of the regions on the same device and process
 - Sync streams to stream events
- Phase VI: Unpack buffers sent with MPI*
 - MPITest while all packages are received
- Phase VII: transfer
 - Initiate unpacking of buffer received on device
 - Sync stream to transfer event for the buffer sent to host
 - Unpack the buffer sent to host

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Applications

- Heat simulation
 - Computes heat transfer equation
 - For each point in 3D space performs 7-point stencil at each timestep
 - 100 timesteps
 - Memory intensive
- Cardiac modeling
 - Simulates the propagation of electrical signals in the cardiac tissue
 - In 2D space uses the Aliev-Panfilov model
 - 1350 timesteps
 - Compute intensive

Performance Study

- All speedups are reported against a baseline
 - Manages memory manually with CUDA
 - Uses pinned memory for host allocations
 - Generates GPU kernels with OpenACC annotations
- In all experiments, the measured time includes
 - Computation
 - And the time required for data transfers between hosts and devices.

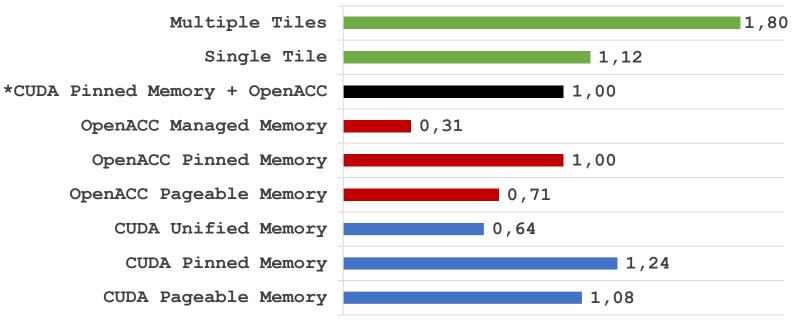
GPU Cluster

Summitdev:

- 54 nodes
 - 3 racks each with 18 nodes
 - Connected in a full fat-tree via EDR InfiniBand
- 108 IBM POWER8 CPUs
 - Each node has 2 CPUs
 - 10 core per CPU
- 216 NVIDIA P100 GPUs
 - Each node has 4 GPUs
 - Connected via NVLink 1.0

Single GPU Performance

Speedup over *Baseline on a Single GPU

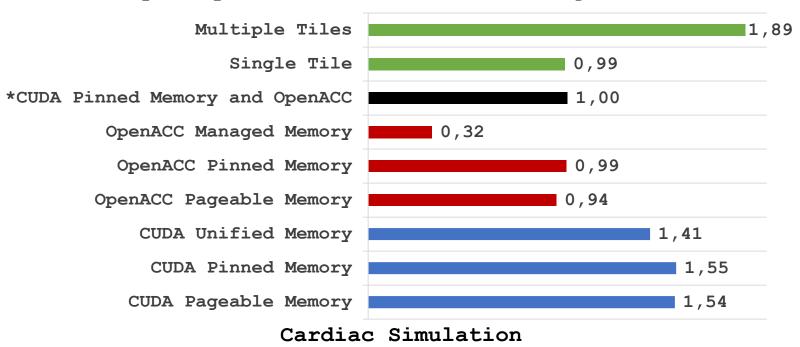


Heat Simulation

- 96% of GPU memory is used
- Multiple tiles: 128
- 80% performance increase with overlapping

Single GPU Performance

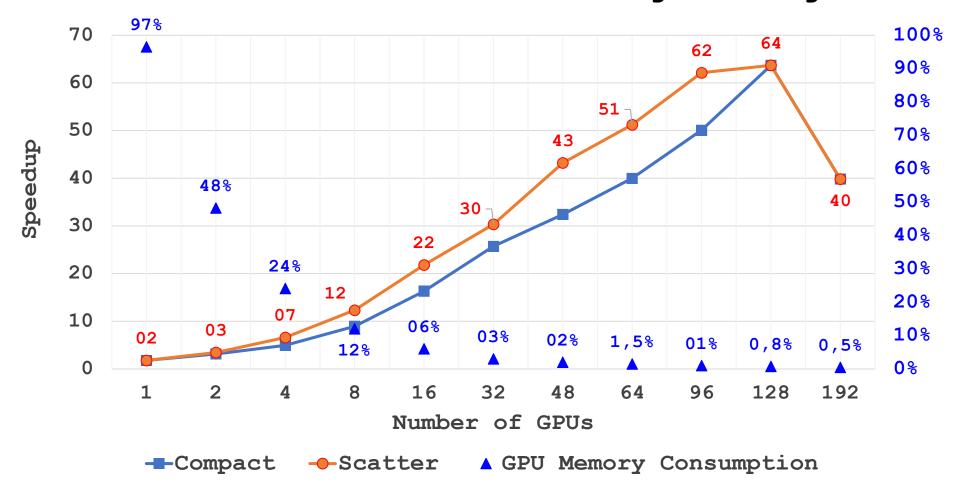
Speedup over *Baseline on a Single GPU



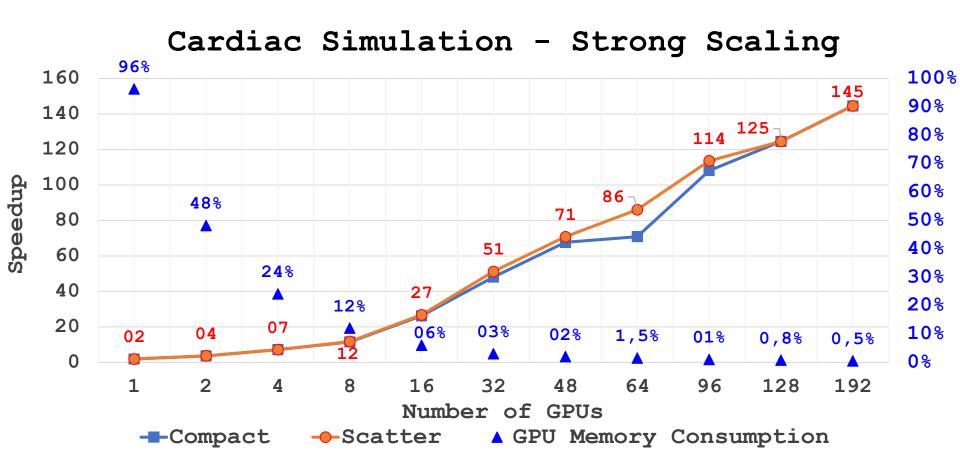
- %96 of GPU memory is used
- Multiple tiles: 81
- 89% performance increase with overlapping

Cluster Performance

Heat Simulation - Strong Scaling



Cluster Performance



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Related Work

- Well-known programming models
 - CUDA, OpenCL: Memory management with functions and low-level kernel implementation
 - OpenACC, OpenMP: Pragma-based programming models
 - No support for GPU Clusters
 - CUDASA, CudaMPI, dCUDA, SnuCL and dOpenCL introduce communication primitives for CUDA and OpenCL
 - I) Wu et al., 2016, II) Aji et al., 2016, etc. modify MPI to optimize communication from GPU memory
 - I) Komoda et al., 2013 and II) Matsumura et al., 2018 extend OpenACC for single-host-multi-GPU systems

Related Work

- Pragma-based other programming models with their in-house compilers
 - I) Unat et al., 2011 and II) Lee and Eigenmann, 2010
 - Difficult to maintain in-house compilers
- Instead of hiding memory management, some works provide highlevel means
 - Thrust, Kokkos, C++ AMP, etc.
- Task-based programming models
 - I) Agullo et al., 2018, II) Grasso et al., 2014, etc.
 - Programmer is responsible from kernel implementations and task scheduling
- Skeleton-based programming models
 - Muesli, Cluster-SkePU, etc.
 - Skeletons arguably reduce programming flexibility

! Most of the studies do not consider the low interconnect bandwidth

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Future Work

- Auto tuning of tile size
- Performance study and auto tuning of hybrid (CPU-GPU) execution

Acknowledgement













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Thank you for listening!

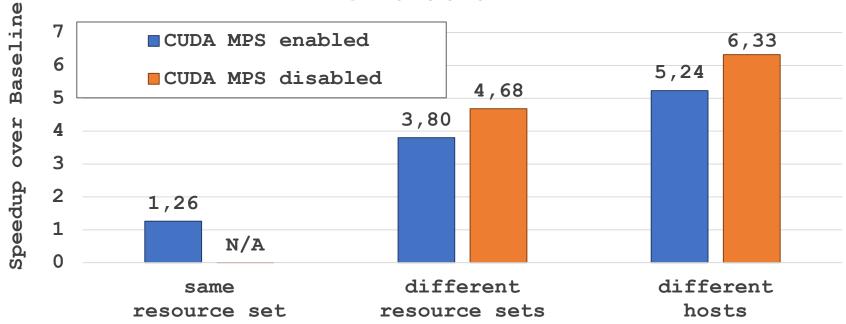
APPENDIX

Summitdev

- Had an issue on GPU Inter-Process Communication
 - Prevented us from conducting experiments with direct communication across the cluster
 - Instead library employed indirect communication
- Configured as exclusive-process, which allows only one process per GPU
 - Also prevents having multiple processes per host if they use pinned host memory
 - To employ multiple processes, CUDA multi-process service (MPS) should be enabled
- Jobs are submitted with resource sets
 - Each GPU can have its own resource set
 - or share the resource set with the other GPUs on the host

Single Host Performance - 4 GPUs

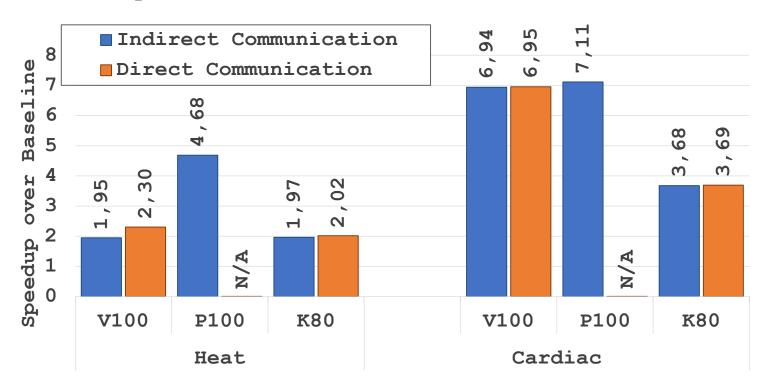
Impact of CUDA MPS and Resource Set on Heat Simulation



- MPS has an overhead
- Separate resource sets for GPUs yield to a better performance

Single Host Performance - 4 GPUs

Impact of GPUDirect on Communication



- Heat shows a slight increase with direct transfers on V100 workstation
 - Employs high-bandwidth NVLink 2.0 between GPUs