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Memory-Aware Scheduling of Tasks Sharing Data on Multiple GPUs with Dynamic Runtime Systems

15th Scheduling for Large Scale Systems Workshop - Fréjus -
Juin 2022

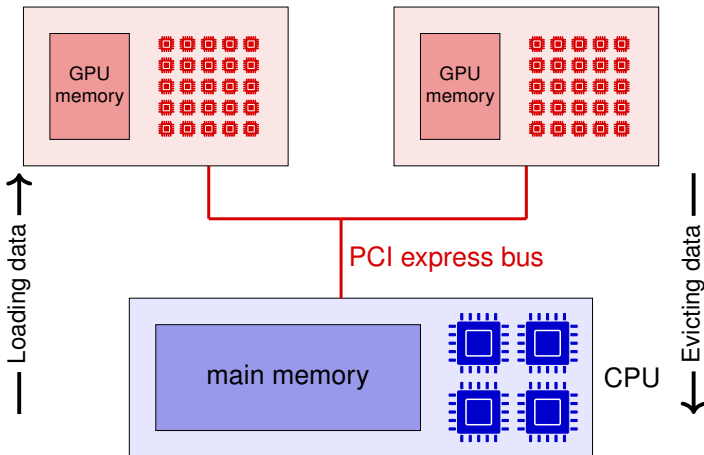
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LIP - ROMA - LaBRI - STORM



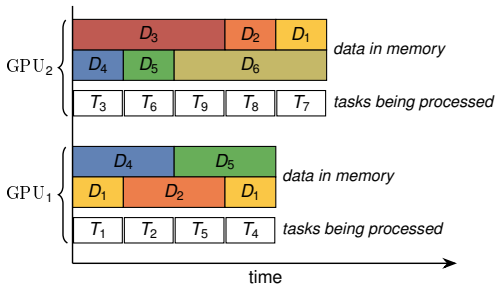
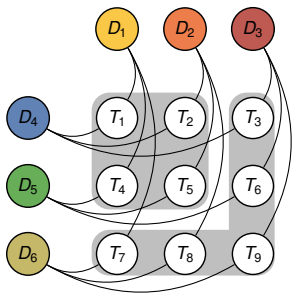
Motivation: Extract peak performances from GPUs



GPUs are fast but have a limited memory

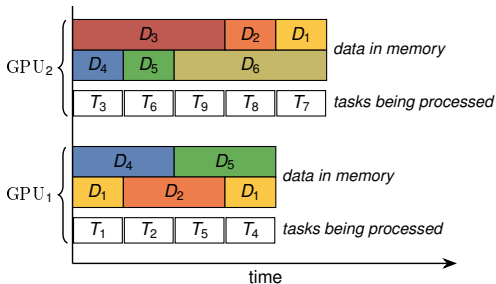
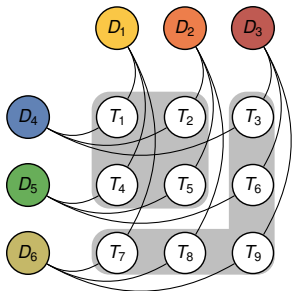
Share the same PCI bus with limited bandwidth

Framework: An example with 2D grid dependencies



- Independent tasks sharing data
- Limited GPU memory

Goal: minimize makespan



- Balancing tasks among GPUs → Reduce total execution time
- Ordering tasks inside each GPU → Reduce data transfers

Problem modeling

GPU_k wants to process task T

- 1 **Evict** selected data (possibly none) from the memory of GPU_k
- 2 **Load** data for T that are not yet in memory
- 3 **Process** T on GPU_k

Hypothesis

- Independant and homogeneous tasks
- Same size data

A bi-objective optimization problem

Objective 1: Load Balancing

minimize \max_k *number of tasks allocated to GPU_k*

Objective 2: Data Movement

Minimize the number of data loads from the main memory:

$\#Loads_k = \sum$ *data load for each T computed on GPU_k*

minimize $\sum_k \#Loads_k$

Algorithms

2 schedulers from STARPU

- EAGER (our baseline)
- Deque Model Data Aware Ready (DMDAR)

1 algorithm adapted from the literature

- hMETIS

Novel algorithm

- Data-Aware Reactive Task Scheduling (DARTS)

Dynamic scheduler of STARPU: DMDAR

Strategy

Schedule tasks so their completion time is minimal based on computation + data movement

+ **Ready** reordering heuristic on GPU_k

input : List L of tasks allocated on GPU_k

while $L \neq \emptyset$ **do**

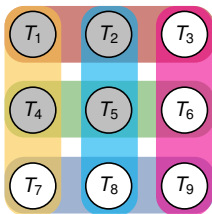
 Search first $T \in L$ requiring the fewest data transfers

 Wait for all data in $\mathcal{D}(T)$ to be in GPU_k memory

 Start processing T

end

Using (hyper-)graph partitioning: hMETIS



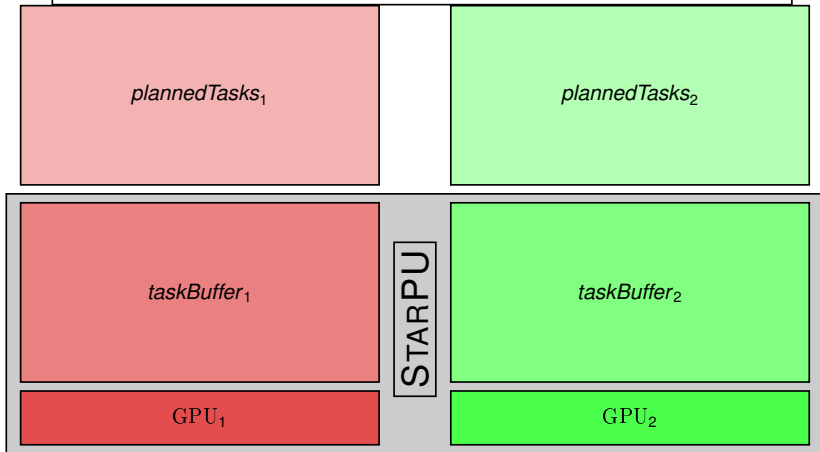
Hypergraph \rightarrow Represent a data being used by different tasks
Accurately represent data sharing

Strategy

- 1 Apply hMETIS to create tasks subsets
- 2 Each subset is allocated to a GPU
- 3 Use the **Ready** strategy
- 4 Dynamic load balancing using task stealing

DARTS: Task flow

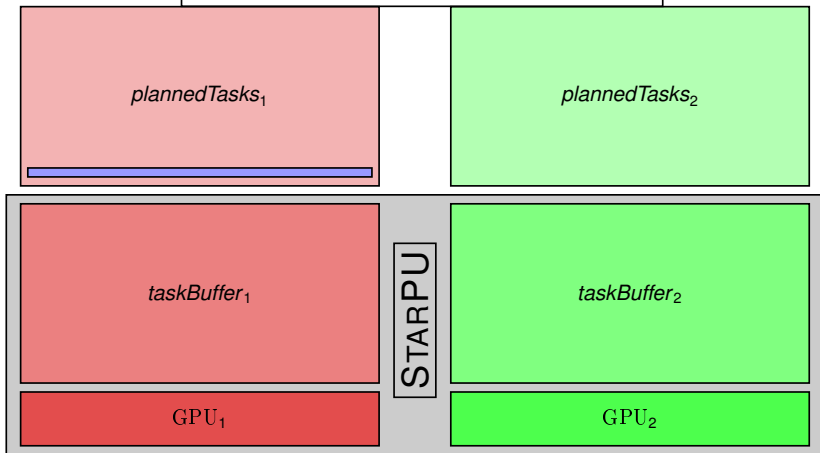
DARTS is demand driven. It uses 2 queues. Task selection detailed next slide.



GPU₁ is asking for a task!

DARTS: Task flow

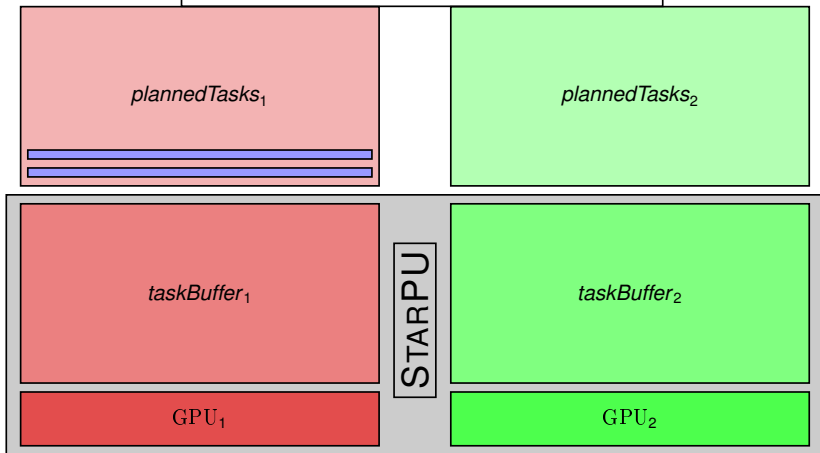
If $plannedTasks_k = \emptyset \rightarrow$ DARTS fill $plannedTasks_k$



GPU₁ is asking for a task!

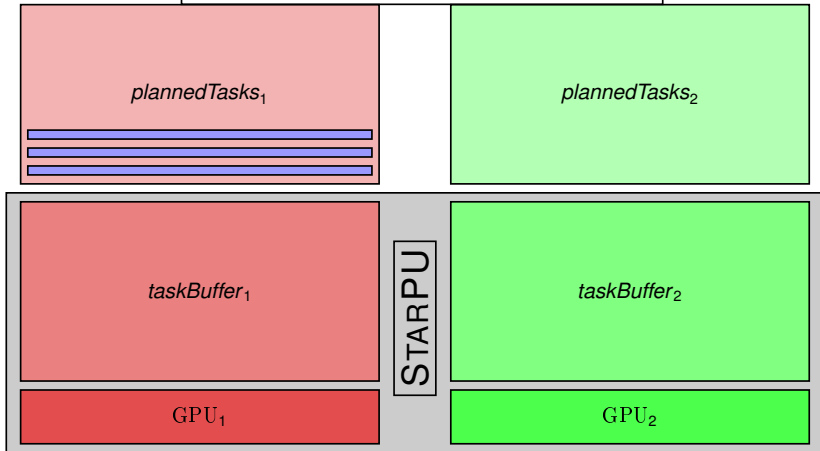
DARTS: Task flow

If $plannedTasks_k = \emptyset \rightarrow$ DARTS fill $plannedTasks_k$



DARTS: Task flow

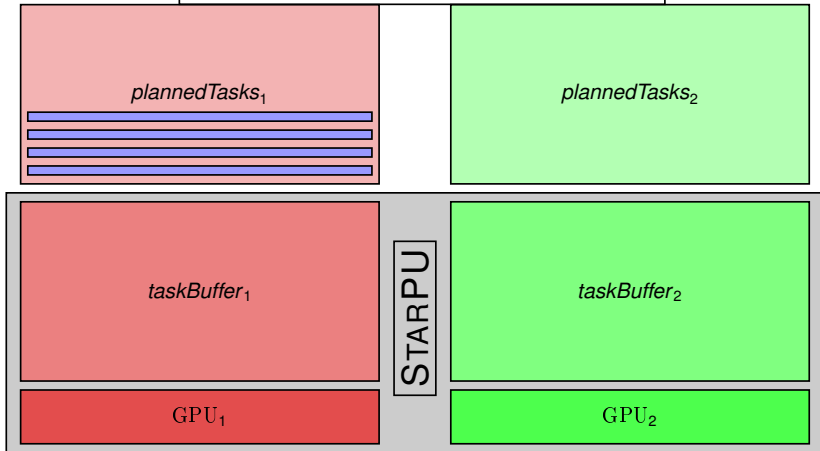
If $plannedTasks_k = \emptyset \rightarrow$ DARTS fill $plannedTasks_k$



GPU₁ is asking for a task!

DARTS: Task flow

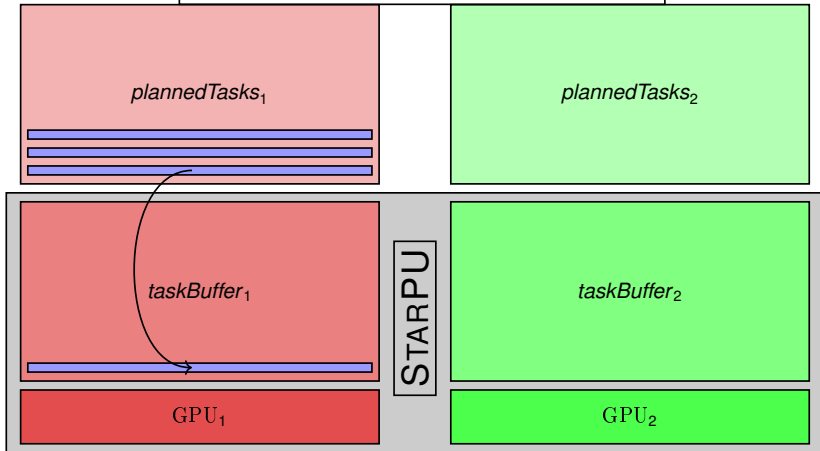
If $taskBuffer_k = \emptyset \rightarrow GPU_k$ will pop $plannedTasks_k$



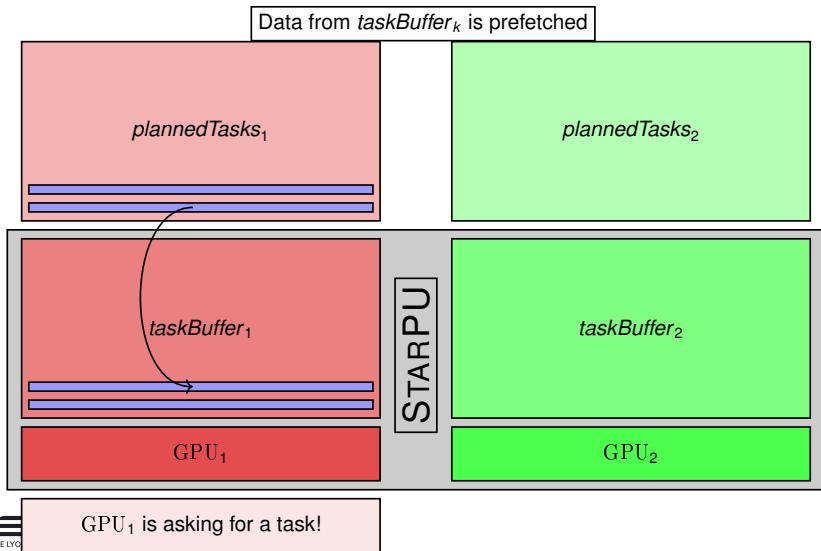
GPU₁ is asking for a task!

DARTS: Task flow

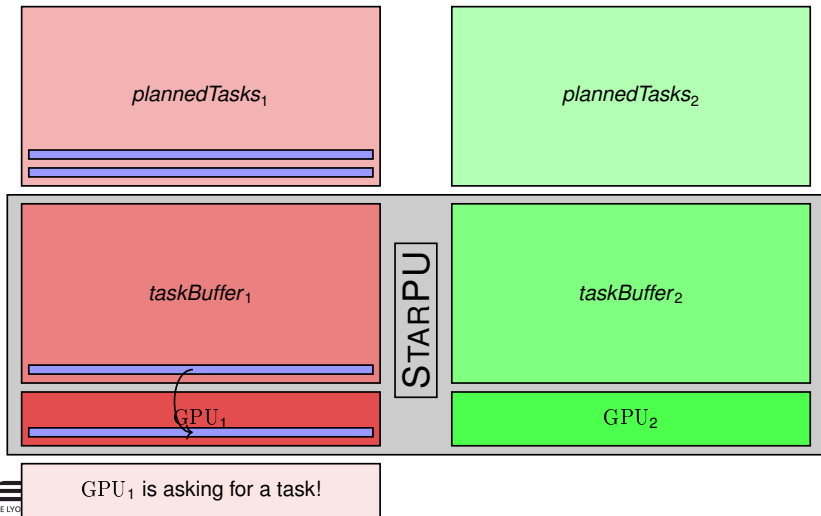
If $taskBuffer_k = \emptyset \rightarrow GPU_k$ will pop $plannedTasks_k$



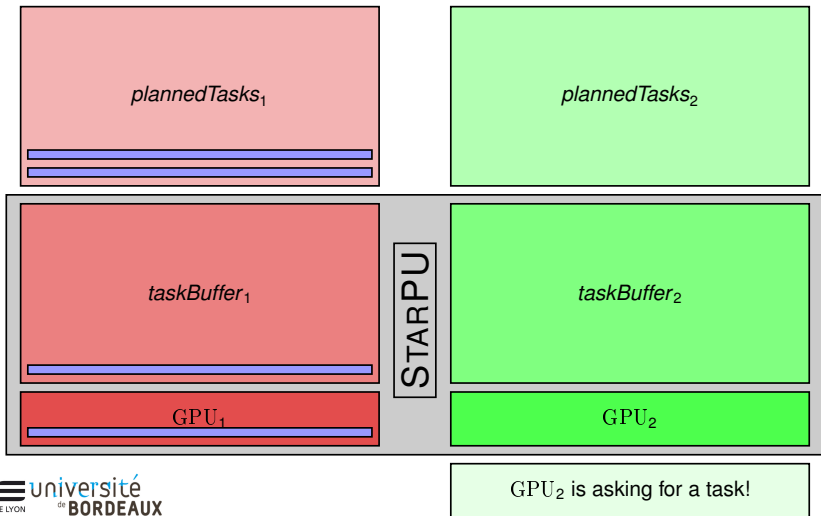
DARTS: Task flow



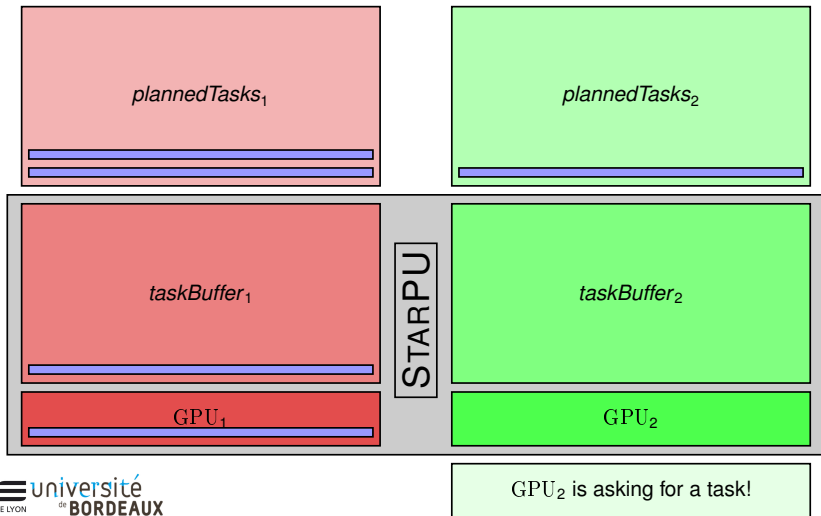
DARTS: Task flow



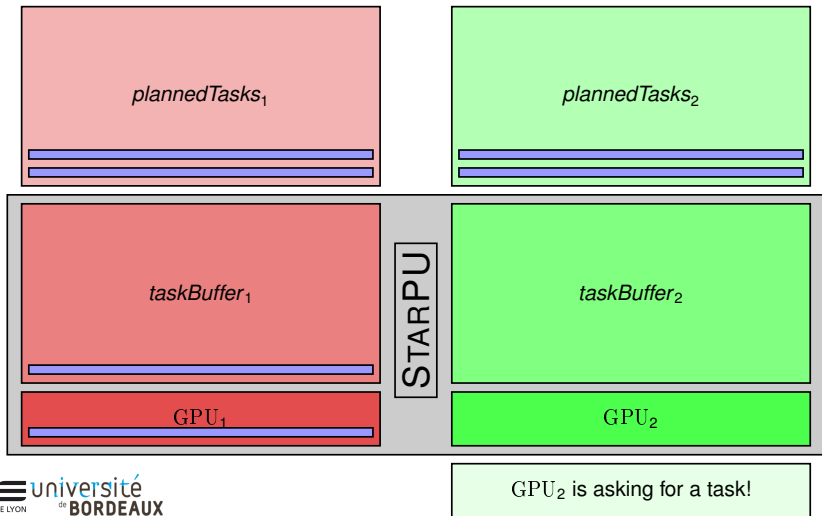
DARTS: Task flow



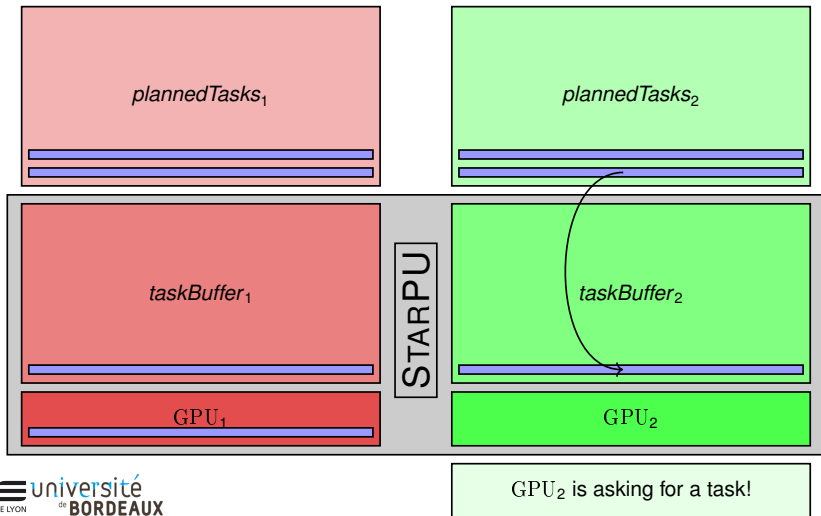
DARTS: Task flow



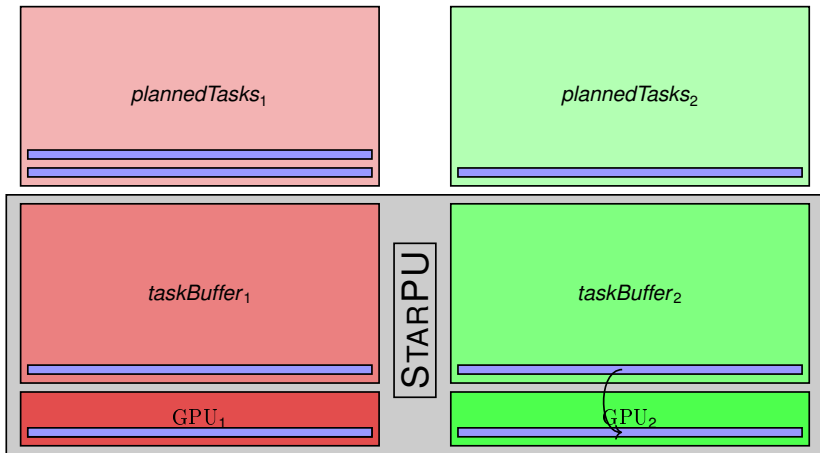
DARTS: Task flow



DARTS: Task flow



DARTS: Task flow



DARTS: Strategy

Intuition: consider data locality before task allocation

Perform as many tasks as possible with the data at hand

When no more available tasks with data at hand:

- Find data $D_{optimal}$ such that the number of tasks depending on $D_{optimal}$ and on other data already in memory is maximum
- $plannedTasks_k \leftarrow$ set of unprocessed tasks depending only on $D_{optimal}$ and on other data already in memory

DARTS: Eviction and optimizations

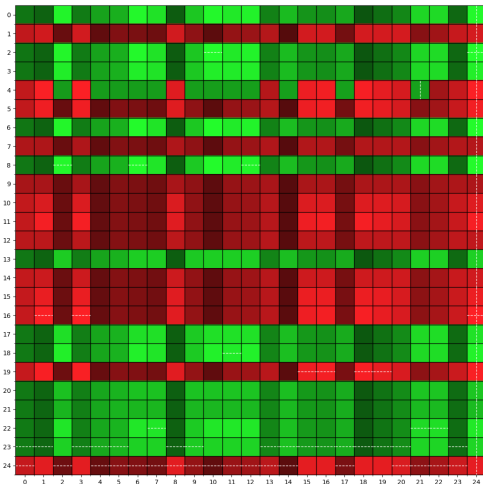
Our eviction policy: LUF (Least Used in the Future)

- 1 If possible, evict data not useful for any task in $taskBuffer_k$ and used by a minimal number of tasks in $plannedTasks_k$
- 2 Otherwise, apply Belady's rule on tasks already allocated
- 3 Update $plannedTasks_k$

Improvements

- **3inputs**: Extension to deal with a heterogenous number of data per task
- **OPTI**: Reduce scheduling complexity by stopping the search for $D_{optimal}$ earlier

Visualization of DARTS processing order on the tiled dense Matrix Multiplication in outer product order



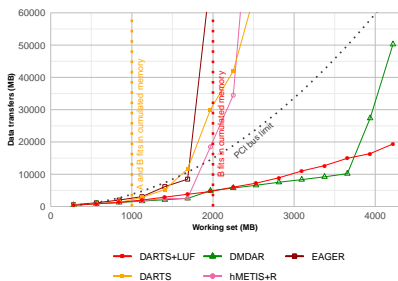
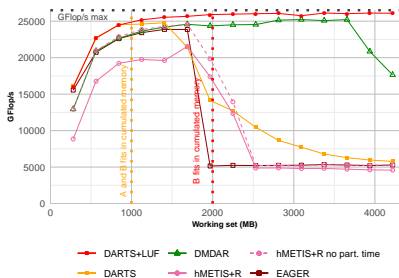
Experimental settings

- Real Tesla V100 GPUs and simulations on Simgrid
- PCI bandwidth not limited (12000 MB/s)
- GPU memory limited to 500 MB → To better distinguish performance on small datasets

Applications

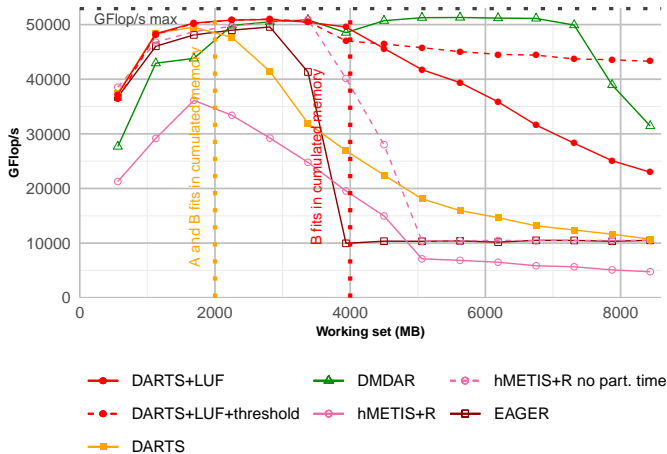
- Tiled $(1 \times n)(n \times 1)$ dense and sparse Matrix Multiplication in outer product order: $C = A \times B$
- Tiled $(n \times n)$ Gemm: $C = A \times B$
- Tiled Cholesky decomposition (without dependencies) ($A = L \times L^T$)

Tiled dense Matrix Multiplication in outer product order with 2 real Tesla V100 GPUs

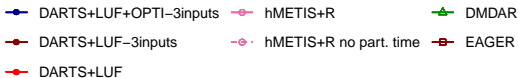
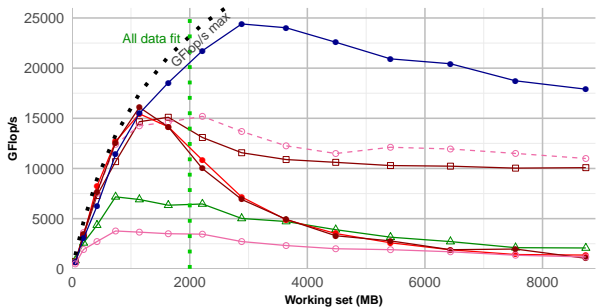


- EAGER, hMETIS & DARTS: Pathological matrix size after the red line
- DMDAR: Conflict between prefetch and eviction
- DARTS+LUF outperforms DMDAR even with more data transfers
 → **DARTS is better at overlapping communication and computations**

Tiled dense Matrix Multiplication in outer product order with 4 real Tesla V100 GPUs

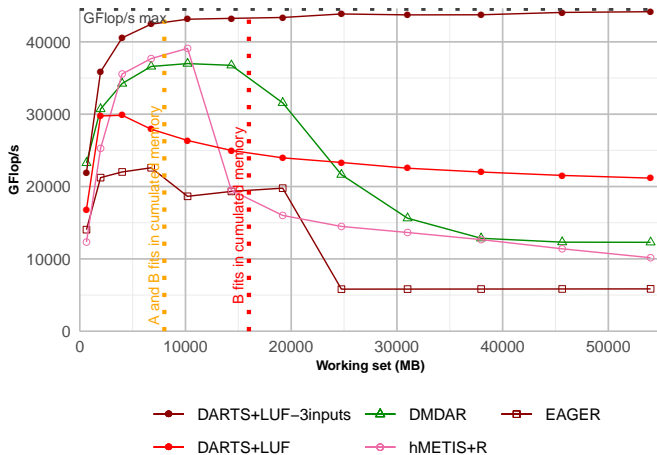


Cholesky decomposition with 4 real Tesla V100 GPUs

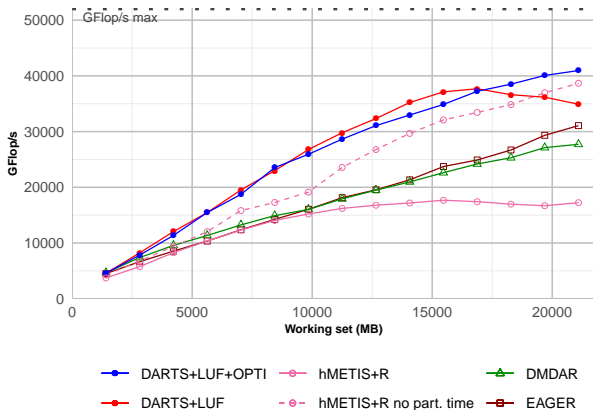


- **OPTI** reduces scheduling time which improves performance
- **DMDAR** suffers from a large scheduling time

Tiled Gemm with 4 Tesla V100 GPUs in simulation



Tiled sparse Matrix Multiplication in outer product order without memory limitation (32GB by GPU) with 4 real Tesla V100 GPUs



- DARTS produces a **processing order that best distributes transfers over time**
- hMETIS suffers from a significant partitioning cost

Conclusion and future work

Limiting data movements is crucial to extract the most out of GPUs

Our contribution → **DARTS+LUF, focused on data locality**

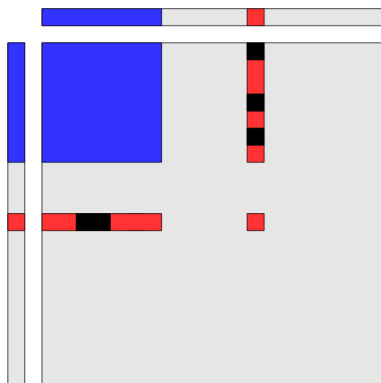
DARTS achieves very good performance because it:

- **Limits data transfers** thanks to the finding of an optimal data and an adapted eviction policy
- **Overlaps** communication and computations by distributing transfers over time
- Can be used with a **reduced complexity**

Areas for improvement

- Reduce computational complexity
- Consider tasks with dependencies
- Take inter-GPU communications into account
- Manage multiple MPI nodes

Dynamic Scheduling Strategies for Matrix Multiplication



Source: Analysis of Dynamic Scheduling Strategies for Matrix Multiplication on Heterogeneous Platforms - Marchal - Beaumont