

Memory-Aware Scheduling of Tasks Sharing Data on Multiple GPUs

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Memory-Aware Scheduling of Tasks Sharing Data on Multiple GPUs

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Why focus on memory-aware scheduling ?



GPUs are quick but have a limited memory

They share the same PCI bus with limited bandwidth



Example with 2D grid dependencies



GOALS:

- Balancing tasks among GPUs → Reduce total execution time
- Ordering tasks inside each GPU → Reduce data transfers
- Having a generic scheduler → Efficient with any application or memory limitation

Dynamic scheduler of STARPU: DMDAR

Strategy

Schedule tasks so their completion time is minimal based on computation + communication times

+ **Ready** reordering heuristic on GPU_k

From the list *L* of tasks allocated on GPU_k , it will search the task $T \in L$ requiring the fewest data transfers



Data-Aware Reactive Task Scheduling: DARTS

The scheduling is done by GPU_k when it needs new tasks.

■ Find D_{opt} ∈ dataNotInMem_k such that the number of tasks depending on D_{opt} and on other data already in memory is maximum (if there is a tie: choose with transfer time, priority of the associated tasks and most total unprocessed task)

■ *plannedTasks*_k ← set of unprocessed tasks depending only on D_{opt} and on other data already in memory

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

- Try to evict a data not useful for any task already in the GPU's buffer.
- Try to evict a data used by a minimal number of tasks in the set of task planned by the scheduler.



2D matrix multiplication with 2 Tesla V100 GPUs



Amount of data transfers on the 2D matrix multiplication with 2 Tesla V100 GPUs



Cholesky decomposition with 2 GPUs



Cholesky decomposition with 8 GPUs



LU with 8 GPUs



Conclusion

Limiting data movements is crucial

→ New strategy: DARTS, focused on data movement

Tested on 2D matrix multiplication, Cholesky decomposition, LU, GEMM and sparse matrix multiplication \rightarrow DARTS can achieves good performance when the memory is not constrained and always get very good performance when it is a scarce resource

Areas for improvement

- Improve computational complexity. It's holding us back to get good performances on Gemms and large matrics of the outer product
- Manage multiple MPI nodes

Export it to other out-of-core applications. DARTS is not specific to GPUs!

If you have an open postdoc position contact me :)

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Memory-Aware Scheduling

Joker slide



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

Sparse 2D matrix multiplication without memory limitation (32GB by GPU) with 4 Tesla V100 GPUs



- No memory constraint
- DARTS produces a processing order that best distributes transfers over time

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Memory-Aware Scheduling