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Maxime Gonthier, Loris Marchal, Samuel Thibault

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Memory-Aware Scheduling of Tasks Sharing Data on Multiple GPUs

Maxime GONTHIER

Supervised by Loris MARCHAL and Samuel THIBAULT
maxime.gonthier@ens-lyon.fr

LIP - ROMA - LaBRI - STORM - Inria
ENS de Lyon - Université de Bordeaux

March 23, 2023
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 $\text{GPU}_k$

From the list $L$ of tasks allocated on $\text{GPU}_k$, it will search the task $T \in L$ requiring the fewest data transfers
The scheduling is done by $\mathbf{GPU}_k$ when it needs new tasks.

- Find $D_{opt} \in data\,Not\,In\,Mem_k$ 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)

- $plannedTasks_k \leftarrow$ 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

![Graph showing performance of 2D matrix multiplication with 2 Tesla V100 GPUs. The x-axis represents the working set size in MB, while the y-axis represents GFlop/s. The graph compares the performance of various scheduling algorithms, including DARTS, DMDAR, DARTS+LUF, and EAGER.]
Amount of data transfers on the 2D matrix multiplication with 2 Tesla V100 GPUs
Cholesky decomposition with 2 GPUs

![Graph showing performance metrics for different algorithms (DARTS+LUF, DMDAR, PaRSEC, EAGER) across various working set sizes (MB). The graph indicates the maximum GFlop/s for different working set sizes, with 'All data fit' noted at the minimum working set size.](image-url)
Cholesky decomposition with 8 GPUs

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Memory-Aware Scheduling

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LU with 8 GPUs

![Graph showing performance of DARTS+LUF, DMDAR, and EAGER for LU with 8 GPUs](image-url)
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 → **DARTS can achieve 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 matrices 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 :) 

Contact:

maxime.gonthier@ens-lyon.fr
http://perso.ens-lyon.fr/maxime.gonthier/
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**