Memory-Aware Scheduling of Tasks Sharing Data on Multiple GPUs
Maxime Gonthier, Loris Marchal, Samuel Thibault

To cite this version:
Maxime Gonthier, Loris Marchal, Samuel Thibault. Memory-Aware Scheduling of Tasks Sharing Data on Multiple GPUs. JLESC 2023 -15th JLESC Workshop, Mar 2023, Bordeaux, France. hal-04090612

HAL Id: hal-04090612
https://inria.hal.science/hal-04090612
Submitted on 5 May 2023

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L’archive ouverte pluridisciplinaire HAL, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d’enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.
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 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
Data-Aware Reactive Task Scheduling: DARTS

The scheduling is done by $\text{GPU}_k$ when it needs new tasks.

- Find $D_{opt} \in data\text{NotInMem}_k$ 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)

- $\text{plannedTasks}_k \leftarrow$ 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 vs. working set size for different scheduling algorithms]

- A and B fits in cumulated memory
- B fits in cumulated memory
- GFlop/s max
- Working set (MB)

Legend:
- DARTS+LUF
- DMDAR
- DARTS
- EAGER

Maxime GONTHIER
Memory-Aware Scheduling
March 23, 2023

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

![Graph showing the amount of data transfers on 2D matrix multiplication with different methods and working set sizes.]
Cholesky decomposition with 2 GPUs

![Graph showing Cholesky decomposition performance with 2 GPUs for different memory working sets. The x-axis represents the working set size in MB, and the y-axis represents GFlop/s. The graph compares performance across DARTS+LUF, DMDAR, PaRSEC, and EAGER methods. The graph highlights the maximum GFlop/s for each method and indicates when the working set fits within the memory constraints.](image-url)
Cholesky decomposition with 8 GPUs

![Graph showing Cholesky decomposition performance with 8 GPUs. The x-axis represents the working set size in MB, and the y-axis represents GFlop/s. The graph compares different schedulers: DARTS+LUF, DMDAR, PaRSEC, and EAGER. The legend is as follows: red square for DARTS+LUF, green triangle for DMDAR, blue diamond for PaRSEC, and orange triangle for EAGER. The graph indicates that all data fit within the working set for the DARTS+LUF scheduler.]
LU with 8 GPUs

![Graph showing performance of different methods with varying working set sizes. The x-axis represents the working set size in MB, and the y-axis represents GFlop/s. Different methods are compared, including DARTS+LUF, DMDAR, and EAGER. The graph indicates that all data fit up to certain working set sizes before performance starts to decrease.](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/
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**