Scheduling of Tasks Sharing Data on GPUs with limited memory

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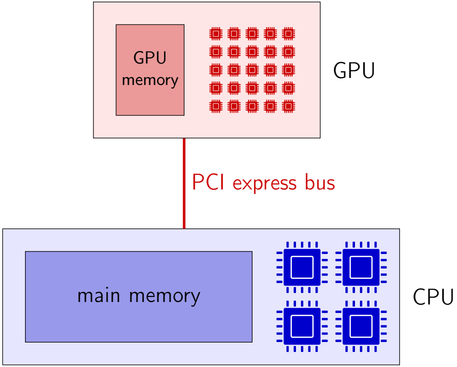
Joint work with Maxime Gonthier & Samuel Thibault (Inria Bordeaux)

New Challenges in Scheduling Theory, Aussois, May 2022.

Platform model



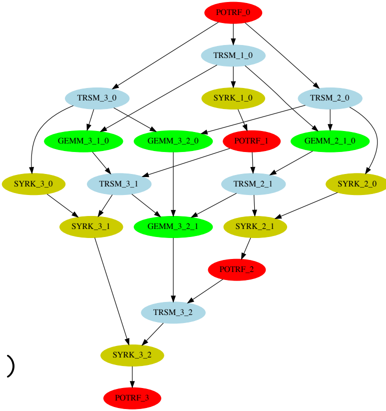
GPUs provide large speed-ups for reduced energy, but:

- limited memory within GPU
- connected through bus with limited bandwidth

Taming HPC platforms with runtime systems

- Write you application as function calls (tasks),
- Specify data input/output (dependencies)
- Provide function codes for specific cores/GPUs
- Let the system do the scheduling at runtime!

```
for(i=0; i<N; i++)
   for(j=0; j<N; j++)
      for(k=0; k<N; k++)
         MULT_ADD(C[i,j], A[i,k], B[k,j])
```



At any time step: consider only available tasks

- Independant tasks
- Sharing some input data

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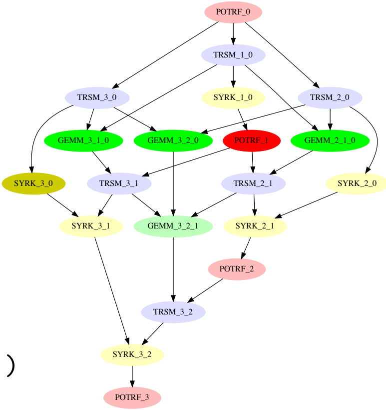
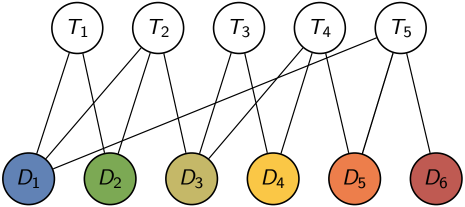
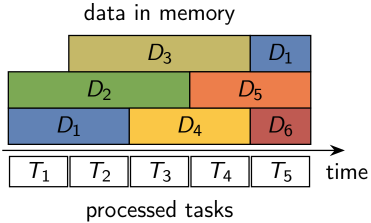


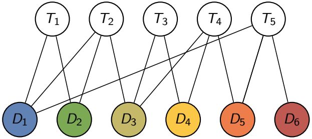
Independant tasks sharing data





- Bipartite graph modeling data sharing among tasks
- Only 3 data allowed in memory (in this example)
- Some data may be evicted/reloaded (D_1 here)

Problem modeling



- Bipartite graph (tasks sharing input data)
- Homogeneous data (size=1)
- Homogeneous tasks (duration=1)
- Limited memory M

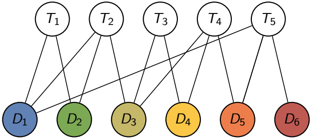
Objective: minimize data loads

Execution framework: repeat these 3 phases

1. Evict some data from the memory
2. Load some new data
3. Compute next task

A priori: complex description of the solution

Problem modeling



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Execution framework: repeat these 3 phases

1. Evict some data from the memory $\rightarrow$ which data to evict?
2. Load some new data $\rightarrow$ which data to load?
3. Compute next task $\rightarrow$ which task order?

A priori: complex description of the solution

Simplifying the solution

Say we decided the task order.

Theorem (straightforward).

Thou shalt load data as late as possible.

$\Rightarrow$ Load (missing) data for a task right before its processing.

Theorem (adaptation of Belady's rule).

Thou shalt evict data whose next usage is the furthest in the future.

Belady's rule: optimal policy for cache management

- Difference: here each task requests several data

So we only need to compute the best task order!

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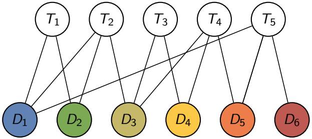
Back to our problem



- Tasks sharing input data
- Limited memory M
- Objective: minimize data loads

Repeat:

1. If needed, evict data used furthest in the future
2. Load missing data for next task
3. Compute next task

Until all tasks are processed.

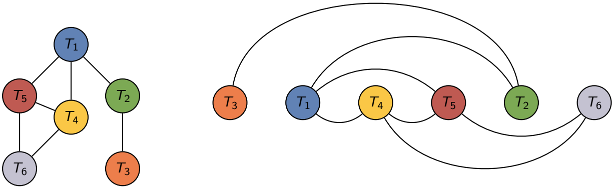
Single question: find task order

Link to cutwidth minimization

Special case:

- Each data shared by at most 2 tasks
- Objective: Load each data exactly once (never evict useful data)

Another graph model: vertices=tasks, edges=data shared among tasks



- Ordering tasks $\Leftrightarrow$ Linear arrangement of vertices
- Amount of data in memory $\Leftrightarrow$ cutwidth
  (maximum number of edges cut by a vertical line)

Our problem is NP-complete by reduction to Cutwidth Minimization.

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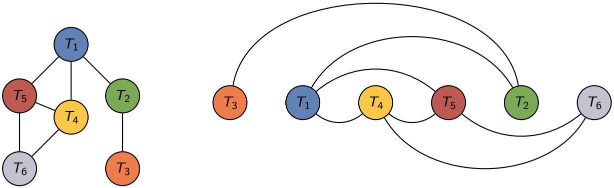

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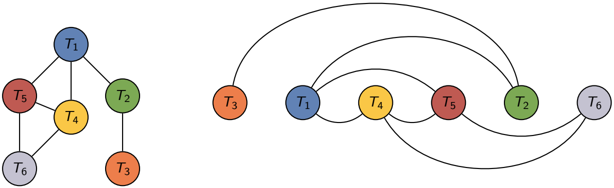

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Building packages of tasks

When the problem is too hard

- Change the problem!

Build packages of tasks sharing a lot of common data

- All inputs within a package fit in memory
- Minimal number of packages

Then, schedule packages one after the others

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- Change the problem!

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Unfortunately, this is also an NP-complete problem ☹

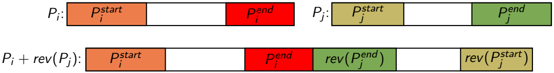
Heuristic to build packages

Hierarchical Fair Packing:

1. Start with each task being a package
2. Merge small packages sharing many input data
3. Stop when total input data exceed memory bound

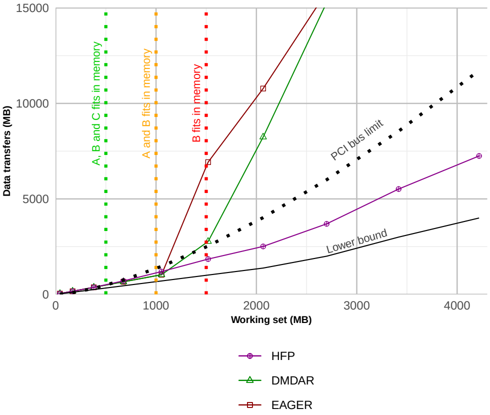
Optimizations:

- Package flipping:
  reverse some package to improve data reuse



- Continue merging packages when the memory bound is reached:
  improve locality among packages

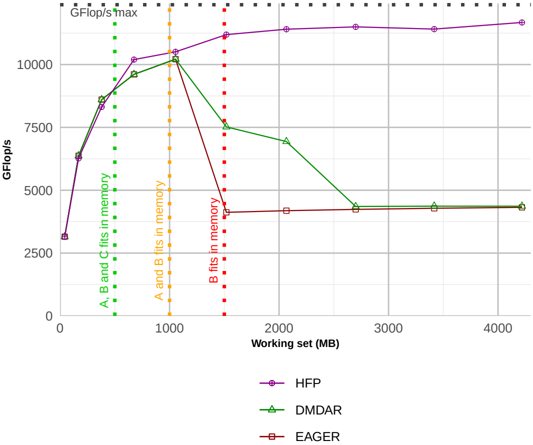
Validation – data movements



- Schedulers implemented in StarPU
- Main competitor: DMDAR (actual scheduler of StarPU)
  - (Allocate tasks to the resource that will complete it the earliest)
  - Reorder tasks at runtime to favor tasks with fewest load requests
- EAGER: follow submission order

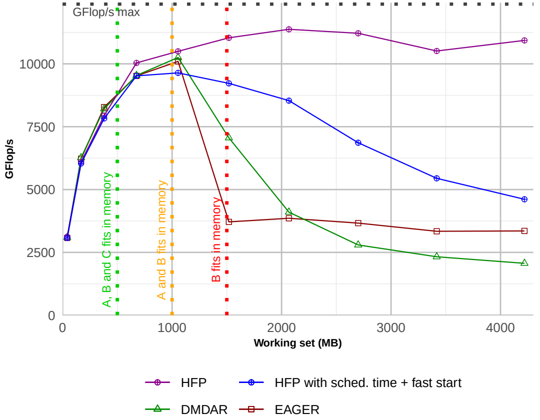
- 3D matrix multiplication
- Data-movements close to the lower bounds
- DMDAR leads to large data-movement as soon as memory is limited

Validation – performance in simulations



- Optimizing data movements allows to keep peak performance even when memory is limited

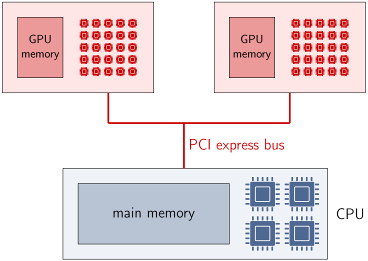
Validation – performance in real experiments



- Performance very similar to simulation for small sizes
- Impact of the complexity for large sizes

Shortcomings & final objective

- Large pre-computation time for large sizes
  (comparing and merging the packages)
- Real objective: distributed setting
  Several GPUs, with their own memory, sharing the bus



Two problems:

- Partition tasks among GPUs
- Order tasks within a GPU

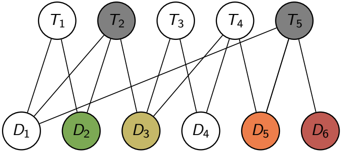
Demand-driven heuristics

Whenever a GPU requires some more work:

- Find the new data that enables the greatest number of available tasks
- Transfer this new data
- Allocate all enabled tasks to the GPU

What about eviction:

- No complete vision of the future ☹
- Window of allocated tasks ☺
- Perform Belady's rule with this limited prediction



DARTS (Data-Aware Reactive Task Scheduling)

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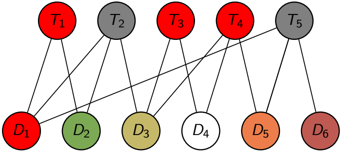
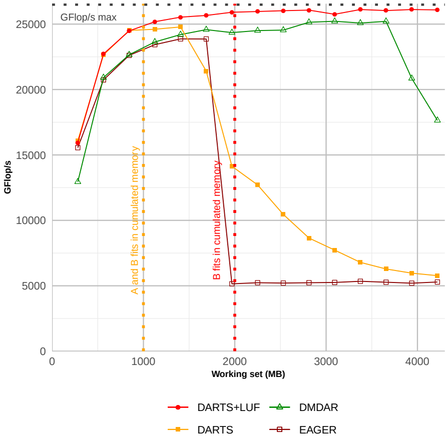


DARTS (Data-Aware Reactive Task Scheduling)

Performance on 2 GPUs (real experiments)



- DARTS is able to achieve peak performance
- Good eviction policy is critical !
  (LUF:adapted Belady's rule, otherwise:LRU)

Conclusion

Take-away messages:

- Concentrate on data movements is the key for performance
- Runtime scheduling of task graphs → independant tasks at each step
- Need for very fast heuristics
  (pre-computation can be allowed)
- Cache management with good knowledge of future requests

Next step:

- Trade-off data locality vs. task affinity (CPU/GPU)