Static vs Dynamic Scheduling Strategies

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Joint work with Emmanuel Agullo, Lionel Eyraud-Dubois, Abdou Guermouche, Julien Hermann, Suraj Kumar, Thomas Lambert, Loris Marchal, Samuel Thibault,...

Scheduling for Large Scale Systems
Nashville, May 19

Outline

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Background: Evolution of parallel hardware

- Multicore chips are commonplace, with complex memory hierarchies
- Heterogeneity seems to be a solid trend
- Many crucial features that are hard to model
  - Many heterogeneous Processing Units
  - With non-symmetric access to the distributed memory
  - Shared communication resources
  - Shared caches
  - Shared access to storage resources
  - Complicated co-scheduling effects
  - + failures, DVFS
- Scheduling is hard

Background – Scheduling Actual Applications

- Start with a code

Algorithm 1 Pseudocode of the tiled Cholesky factorization

```
for k = 0 to n − 1 do
    A[k][k] ← POTRF(A[k][k] RW)
    for i = k + 1 to n − 1 do
        A[i][k] ← TRSM(A[k][k] R, A[i][k] RW)
    end for
    for j = k + 1 to n − 1 do
        A[j][j] ← SYRK(A[j][k] R, A[j][j] RW)
        for i = j + 1 to n − 1 do
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        end for
    end for
end for
```
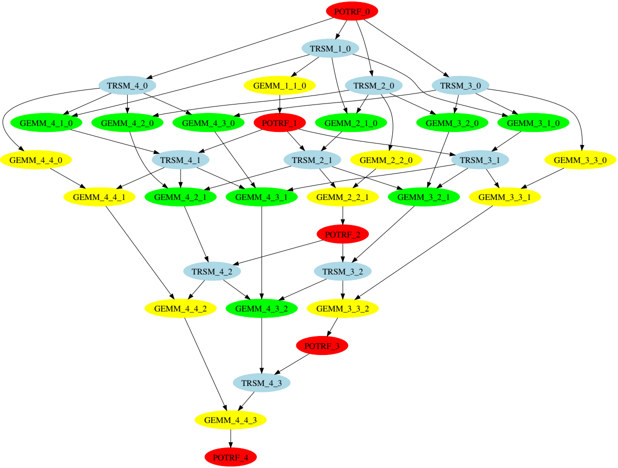
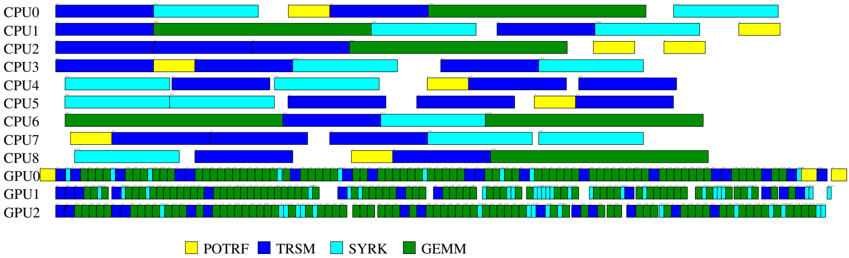

Background – Scheduling Actual Applications

- Start with a code
- Build the task graph



Background – Scheduling Actual Applications

- Start with a code
- Build the task graph
- Find the resource allocation and the schedule



Background – Scheduling Actual Applications

- Start with a code
- Build the task graph
- Find the resource allocation and the schedule
- Limitations (for Cholesky)
  - Heterogeneity makes things harder
  - Simplifying models (co-scheduling effects, bus sharing,...)
  - Needs to be done again for any new architecture !

Background: Can we rely on Static Schedules ?

- Scheduling and resource allocation are hard in general
- and there exist many uncertainties.
- Thus, deciding in advance
  - where to place tasks
  - when/in which order executing them

  can make the system very slow (due to idle times).
- Makes the use of classical static strategies questionable

Solutions to Cope with Uncertainties

- On the theoretical side: robust scheduling
  - Given probability distribution of execution/transfer durations
  - Find (allocation/schedule) that minimizes expected makespan
  - Bad point: makes optimization problems even extremely harder (see Erik's talk) !
- On the practical side: runtime systems
  - Fault Tolerance: checkpointing, replication
  - Scheduling and Load Balancing:
    Mostly dynamic greedy strategies
    (e.g. Hadoop, PaRSEC, StarSs, KAAPI, StarPU)
  - where runtime decisions are based on
    - state of the resources
    - estimations of processing & transfer times
    - add static priorities to choose between ready tasks

Goal in this talk

- Dynamic Strategies:
  - What is the impact of deciding at runtime (myopic vision) ?
- Static Strategies :
  - What is the impact of bad estimations (astigmatic vision) ?
- Combining both ?
  - How to model the behavior of dynamic schedulers ?
    - Balls into Bins games, Power of Two choices, Ordinary Differential Equations
  - Can inject static knowledge into dynamic schedulers ?
    - Affinities between tasks and resources, Specific Dynamic Policies
  - Can inject dynamic adaptations into static schedulers ?
    - Change local ordering, Work Stealing

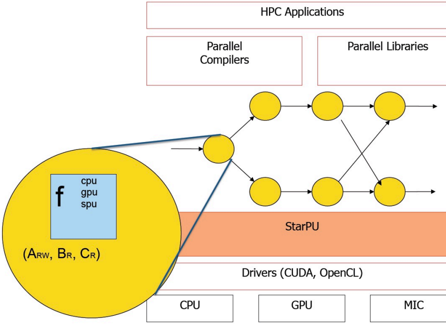
Focus on three basic kernels only

- Map(Reduce) Tasks (with LM and SI)
  - No dependencies, input data already replicated (HDFS, GFS),
  - Focus on the impact of replication.
- Matrix Multiplication (with Thomas Lambert, LED, AG)
  - Tasks are independent but depend on input files
  - Focus on data transfers
- Cholesky Factorization (with Suraj Kumar, EA, LED, AG, JH, ST)
  - 4 different kernels, dependencies, unrelated execution times,
  - But it is easy to overlap communications
  - Focus on the impact of non-uniformity.

Outline

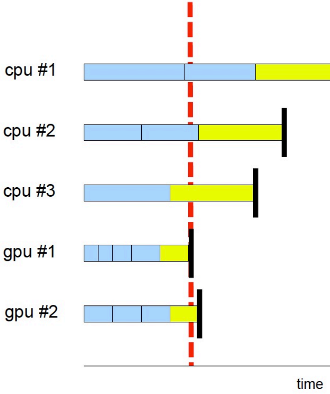
Runtime Systems (StarPU)

- Dynamically
  - Perform Load Balancing
  - React to Hardware Feedback
- Tasks (may) have multiple implementations
  - Upper layers: how data are accessed

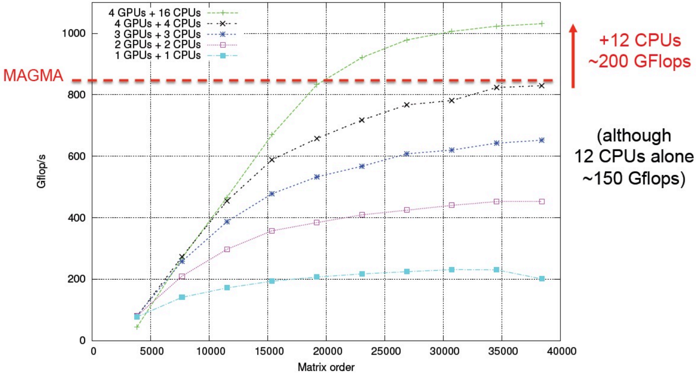


StarPU policy: Basic Idea

- Allocate tasks to resources in advance
  - Overlap Comms with Computations
- When a task becomes ready
  - ie its dependencies are released
- Try all possible resources
- Estimate ending time based on
  - expected running time based on history, parametric cost-model,...
  - expected release time of the resource
  - expected transfer time
- choose the resource with smallest expected completion time



StarPU po



- MAGMA with use of GPUs only (+1 CPU per GPU)
- some kind of super-linear speedup
  - sgeqrt: CPU 9Gflops, GPU 30 Gflops, speedup x3
  - somqr: CPU 9Gflops, GPU 230 Gflops, speedup x27
  - StarPU: 20% of sgeqrt on CPUs, 93% of somqr of GPUs
- **Heterogeneous architectures are cool !**

Outline

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MapReduce basics

- Well known framework for data-processing on parallel clusters
- Popularized by Google, open source implementation: *Apache Hadoop*
- Large data files split into chunks that are
  - scattered on the platform
  - replicated using HDFS for Hadoop
  - there is a time for replication and a time for execution
- Basic Dynamic Scheduling Strategy
  - When a Map slot is available on a processor
  - Choose a local chunk if any
  - Otherwise choose any unprocessed chunk and transfer data

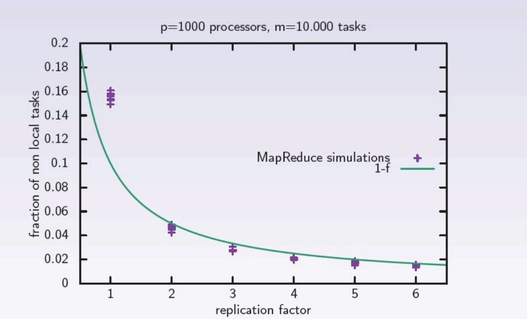
A few remarks

- If all execution times were known (and rather homogeneous)
- and if the application was the only one to execute at runtime
  - the problem would be relatively easy to solve
  - (Ok, still NP Complete but easy to efficiently approximate under realistic assumptions)
- Replication is used
  - for fault tolerance (a little bit)
  - to improve task localilty at runtime (mostly)

Outline

Impact of Replication

- Rationale:
  - the higher is replication ratio (typical value is 3)
  - the higher is the fraction of local tasks (without data transfers)
  - More chances to get executed locally



- Replication is efficient
  - 16% of non local communications without replication
  - $\leq 5\%$ when $r = 2$

Better model: Makespan without replication

- Without replication: each chunk is on a single processor
  - Processor execution time = sum of chunk sizes
  - Similar to the maximum load of a bin in balls-in-bins:
- With homogeneous tasks, when p is close to n,

$$M \sim \frac{\log p}{\log\left(\frac{p \log p}{n}\right)} \text{ whp, } \log p \text{ times the expected value !}$$

- With heterogeneous tasks, see [Raab & Steeger'13], [Berenbrick'08]

Better model: Makespan WITH replication

- Closely related to Balls-In-Bins distribution with r choices:
  - For each ball, select r bins at random
  - Allocate ball to the least loaded bin among them
  - Also known as the power of 2 ($r = 2$) choices
- Balls-In-Bins with multiple choices:
  - For ball B_i, place B_i in least loaded bin with indexes in RC_i

  Rem: load-balancing during the allocation, known weights
- Modified MapReduce:
  - For task T_i, place a copy of T_i on procs with indexes in RC_i
  - When processor P_k becomes idle, execute a local task (if any)

  Rem: load-balancing at runtime, no need to know the weights !

Theorem.

The makespan of Modified MapReduce is equal to the maximum load of Balls-In-Bins with multiple choice

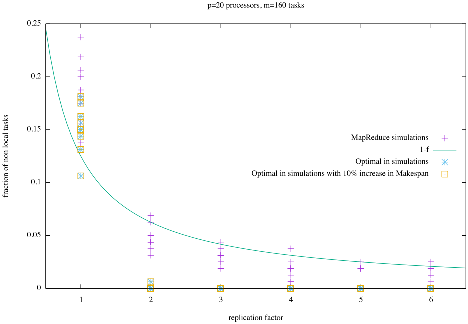
Outline

Impact of Dynamic Scheduling

- Randomized replication
  - Randomization is necessary due to (possibly huge) delay between data allocation and execution
  - is "cheap" (since it is done offline)
  - dramatically reduces the number of communications
- Can we do better at runtime ?
  - once the allocation is known
  - can we pre-compute affinities between tasks and resources
  - for each processor, set of preferred local tasks
  - *ie* tasks it would have run if everything was stable, homogeneous,...
  - run non preferred local tasks if all preferred tasks have been executed

Injecting Static Knowledge in Dynamic Schedulers

- How to compute preferred tasks ?
  - for homogeneous tasks
  - $b-$ matching problem amenable to a flow problem
  - can even be solved in polynomial time.



- Conclusion:
  - as soon as $r = 2$, almost all tasks can be executed locally
  - without changing the makespan !

Outline

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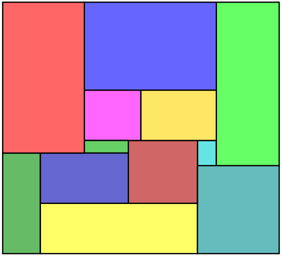
Optimization Problem [IPDPS'16] T. Lambert+ [EuroPar'16]

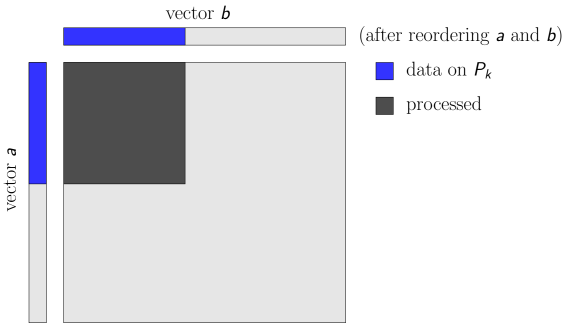
- Problem: partition the square $[0;1] \times [0;1]$ so that
  - $x_k \times y_k = s_k$
  - $\sum_k (x_k + y_k)$ is minimized
  - Lower bound: $2 \sum \sqrt{s_k}$



- NP-Complete, introduced in 2001
- Approximation Ratio $\frac{7}{4}$, then $\frac{5}{4}$ (Nagamochi et al.)
- then $\frac{2}{\sqrt{3}} = 1.15$ (Armin Fügenschuh) under strong conditions (that do not hold true for CPU-GPU platforms)
- We built a $\frac{2}{\sqrt{3}} = 1.15$ approx algorithm without conditions (based on ugly, long and technical proof), can be generalized to cube partitioning.

Outline

StarPU Dynamic Strategy [HPDC'14]



StarPU data-aware strategy DYNAMIC:

Idea : favor tasks for which processors already hold some data.

1. When P_k requests a task, send a new couple (a_i, b_j) to P_k
2. Allocate all available tasks $a_i \times b_{j'}$ (for $b_{j'}$ already on P_k) Allocate all available tasks $a_{i'} \times b_j$ (for $a_{i'}$ already on P_k)

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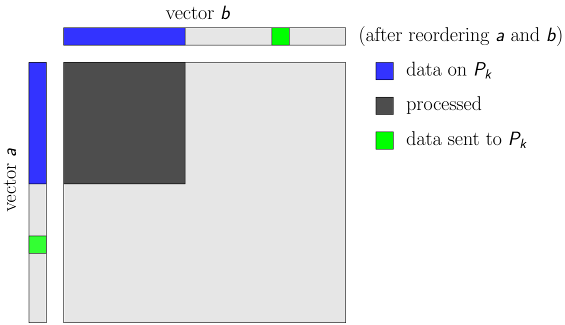

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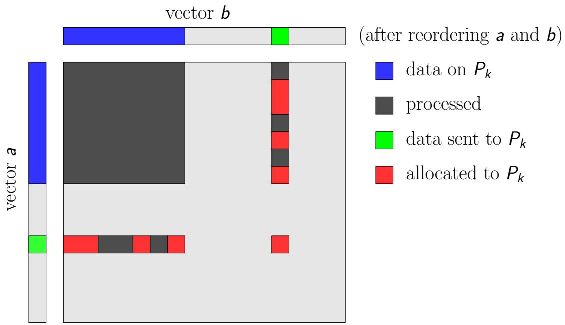

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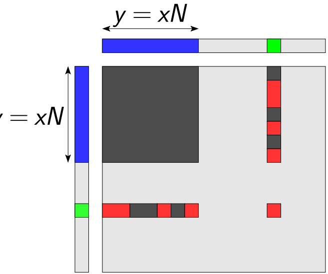
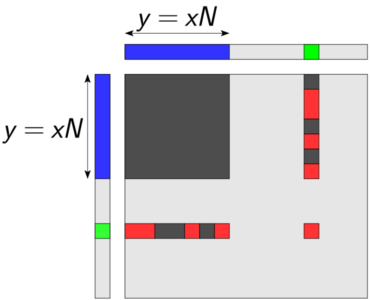
Dynamic2Phases: Analysis (I)

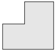
- Assume that the size N of both vectors is large
- Consider a fluid relaxation
- Describe the continuous system using Ordinary Differential Equations



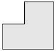
- Ratio $x = y/N$ of elements of a and b on P_k at $t_k(x)$
- Basic step: when this ratio goes from x to $x + \delta x = y/N + \ell/N$
- In ■ : all tasks processed (by P_k or other processors)

Dynamic2Phases: Analysis (II)



- In  : $g_k(x)$ is the fraction of unprocessed tasks (assumed uniformly distributed)
- Time for P_k to compute the red tasks:

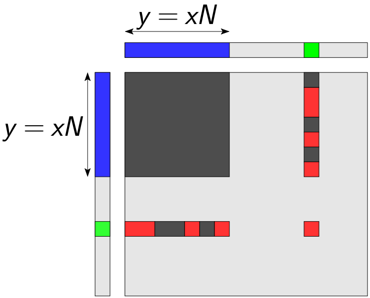
$$\frac{2x\ \delta x\ g_k(x) N^2}{s_k} = t_k(x+\delta x) - t_k(x)$$

- Number of tasks from  computed by other processors during this step: $(t_k(x+\delta x) - t_k(x)) \sum_{i \neq k} s_i$
- Evolution of $g_k(x)$:

$$g_k(x+\delta x) - g_k(x) = g_k(x)\delta x \frac{-2x\alpha_k}{1-x^2} \quad \text{where } \alpha_k = \frac{\sum_{i\neq k} s_i}{s_k}$$

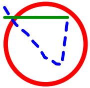
$$\Rightarrow \quad g_k(x) = (1-x^2)^{\alpha_k}$$

Dynamic2Phases: Analysis (III)

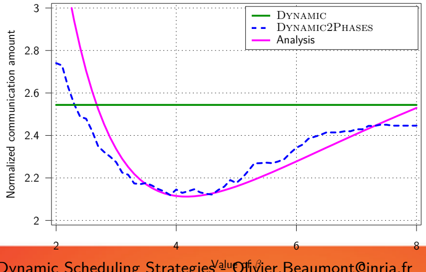


- determine $h_k(x)$, the number of the tasks
  - in the grey area
  - but not processed by P_k
- h_k is solution of a simple ODE.
- that can be used to determine when to switch between strategies
- It works very well in practice !

- Comparison discrete execution vs. continuous analysis:

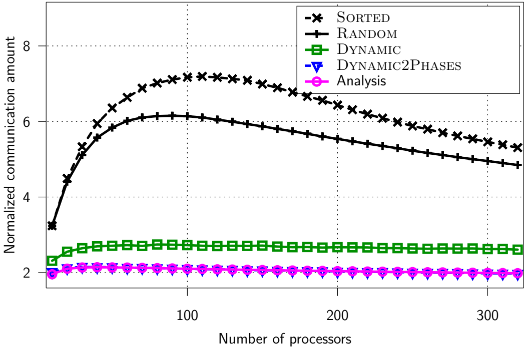


$\Rightarrow$



Add static knowledge in Dynamic Strategies

Comparison with previous heuristics:



- When to switch can easily be computed at runtime
  - and be injected in StarPU scheduling policy
  - $\rightarrow$ add application-dependent knowledge to dynamic policy
- About $2\times$ lower bound on the communication amount
  - Is it good or bad ?

Outline

Comparison of Static and Dynamic [SBACPAD'15]

- Static Strategies are bad...
  - to cope with unexpectedly slow resources
- but they are clever !
  - Worst Case 1.15
  - Average Case < 1.05

- Dynamic Strategies are good
  - to cope with uncertainties
- but they are not so clever...
  - Basic Dynamic: 2.5
  - Dynamic2Phases: 2

Setting for Comparison

- Wrong processing estimation times given to Static
- Force makespan through Work Stealing (keep resources busy)
- Bad Estimations + Work Stealing induce extra data transfers

Comparison of Static and Dynamic Strategies

- Static but wrong processing estimation times
  - Uniform .8 or .95,
  - Gaussian with 0.1 to 1 variance
  - Makespan (either 1 or 2) or (either 1 or 10)
- Node
  - Quasi homogeneous platform with 20 processors
  - heterogeneous with 10 CPUs + 4 GPUs
- And the winner is...

Comparison of Static and Dynamic Strategies

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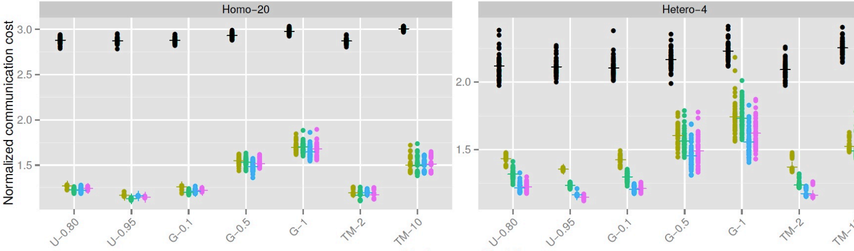
- Node
  - Quasi homogeneous platform with 20 processors
  - heterogeneous with 10 CPUs + 4 GPUs
- And the winner is... **Static !**
- black is dynamic, colored are hybrid
  (static distribution + WS to cope with uncertainties)



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Task Based Cholesky Factorization

Algorithm 2 Pseudocode of the tiled Cholesky factorization

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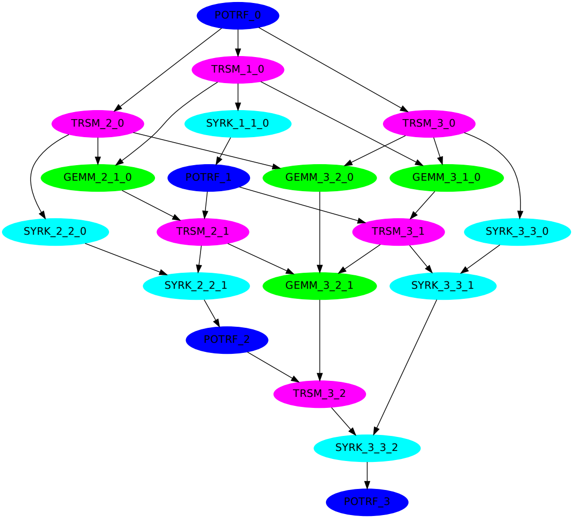
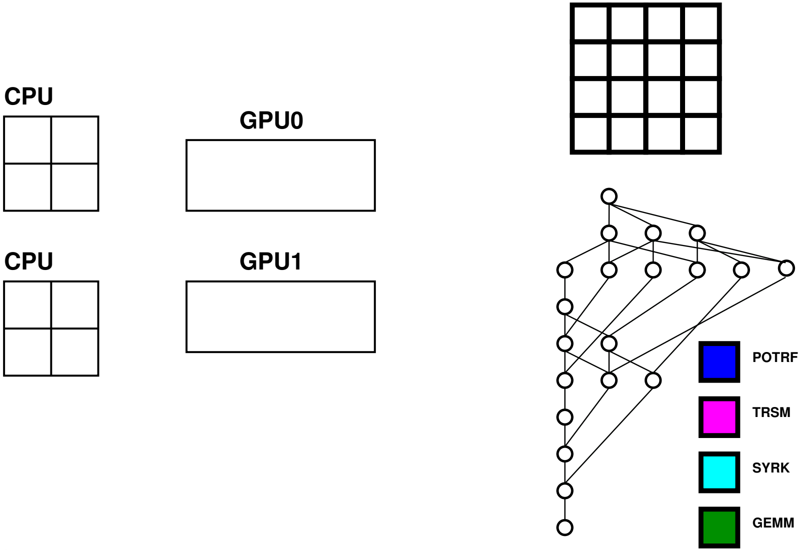
Cholesky task graph



Scheduling of Cholesky tasks with StarPU



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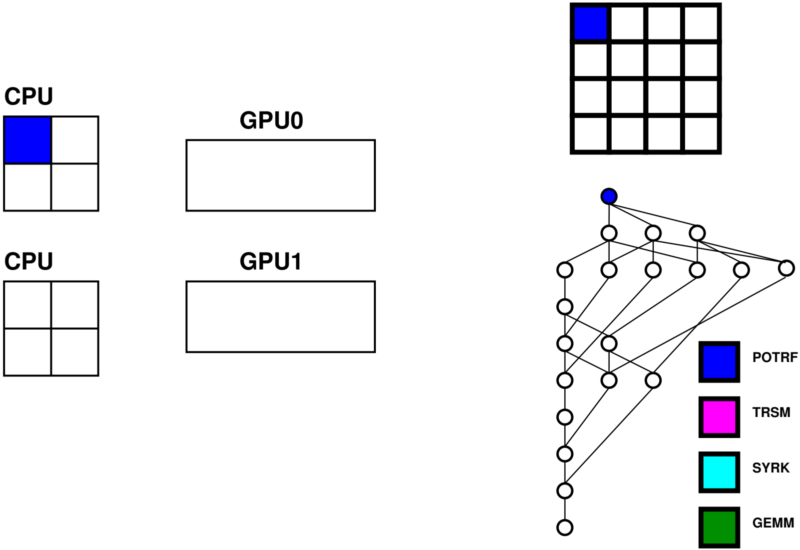

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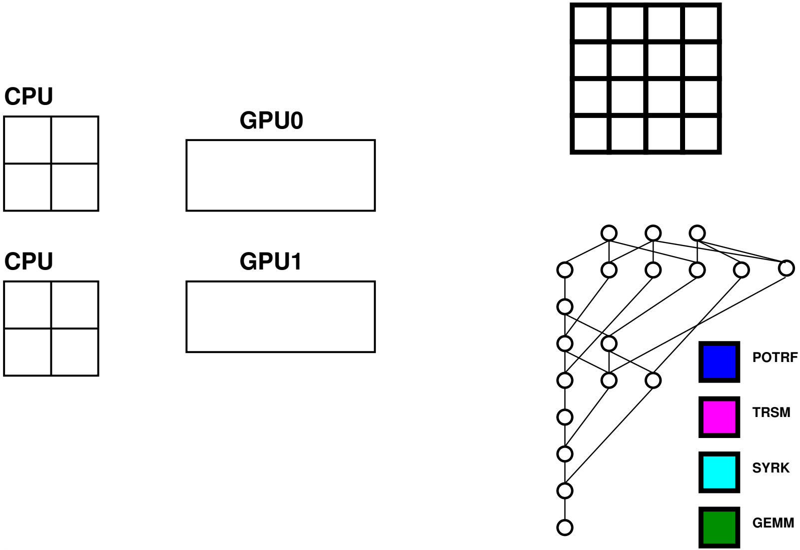

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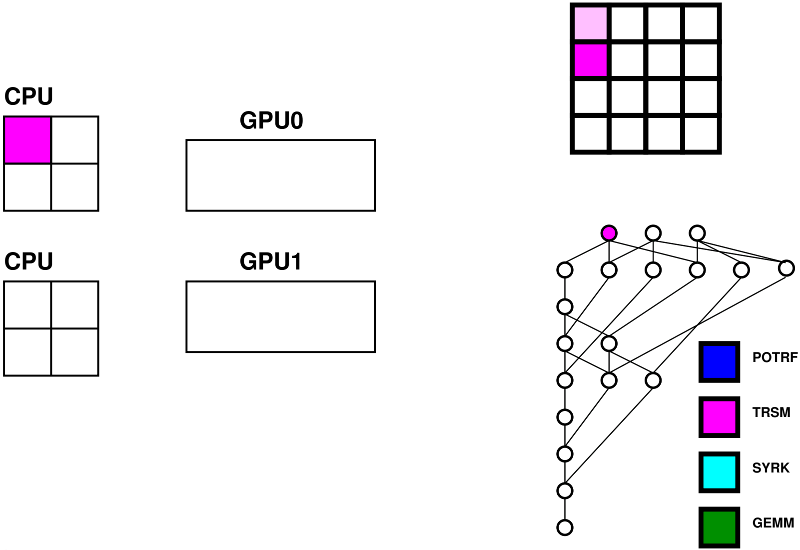

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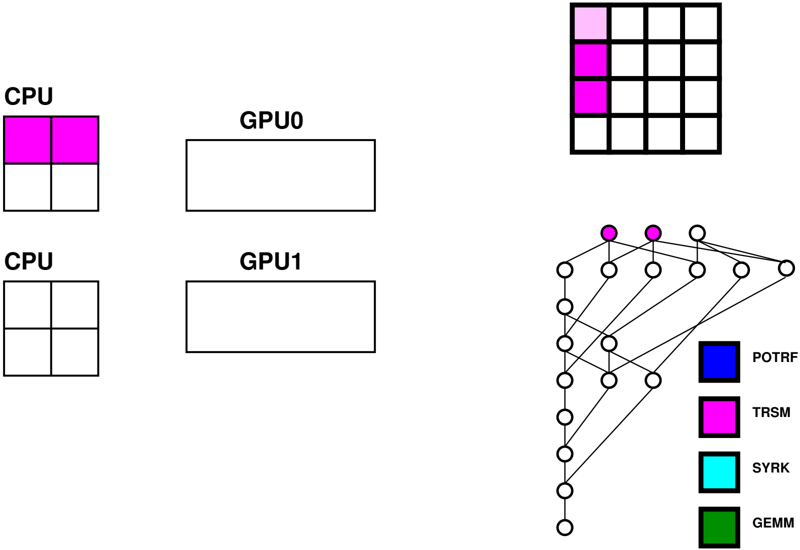

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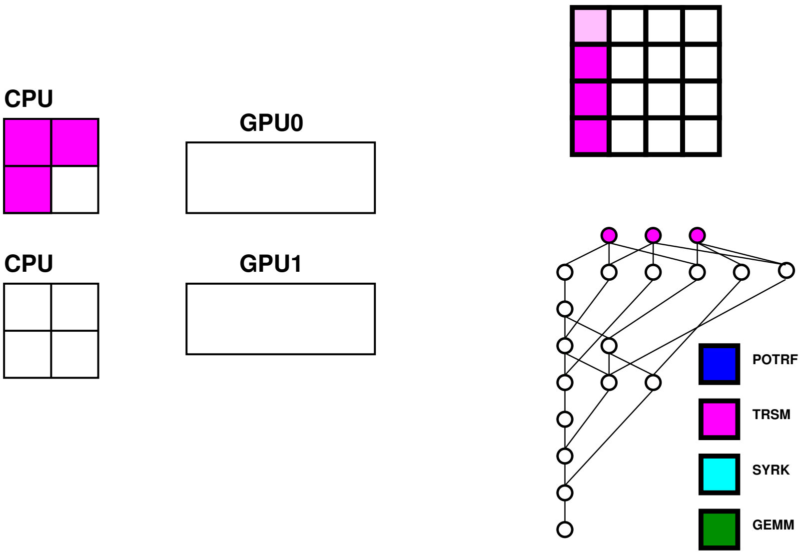

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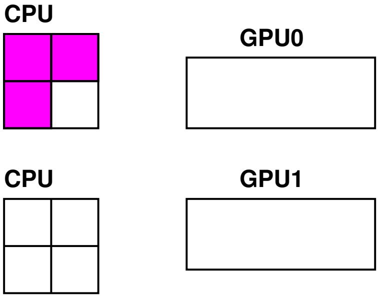
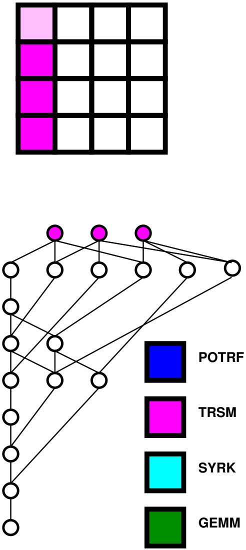


- Handles dependencies



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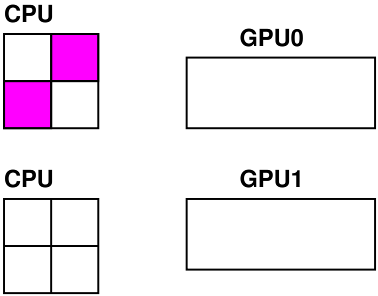

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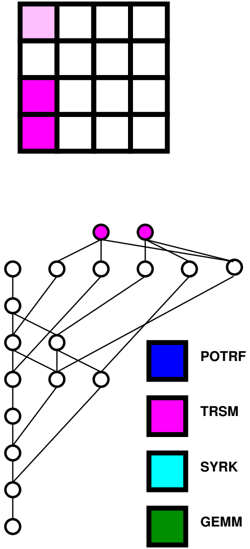

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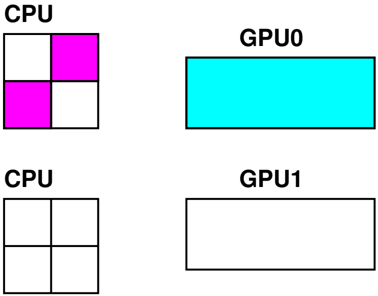
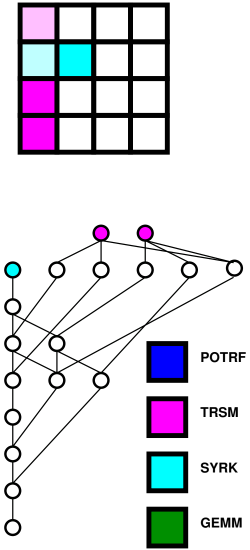
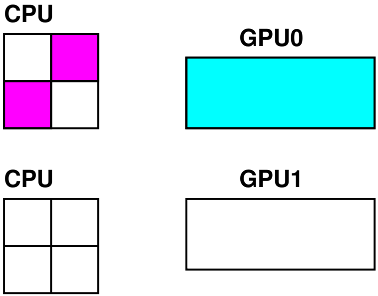
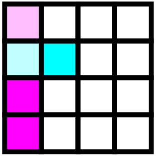


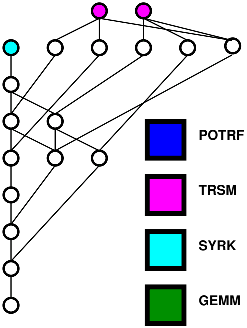


- Handles dependencies

Scheduling of Cholesky tasks with StarPU

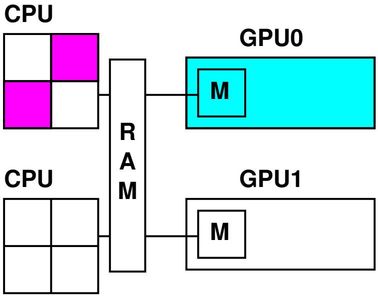


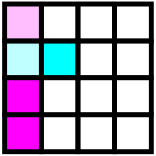


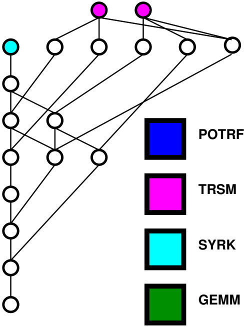


- Handles dependencies
- Handles scheduling (e.g. HEFT)

Scheduling of Cholesky tasks with StarPU







- Handles dependencies
- Handles scheduling (e.g. HEFT)

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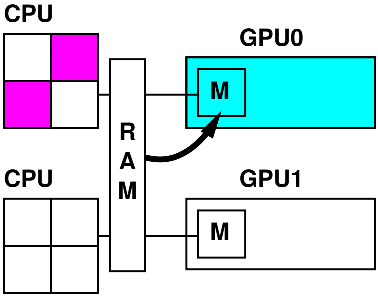

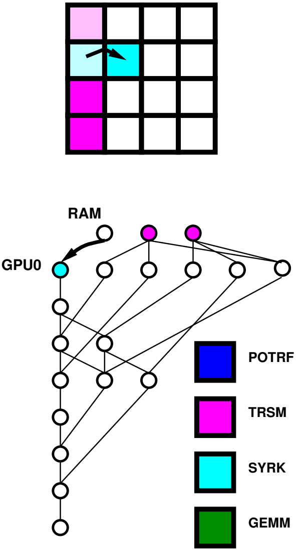

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Machine Information

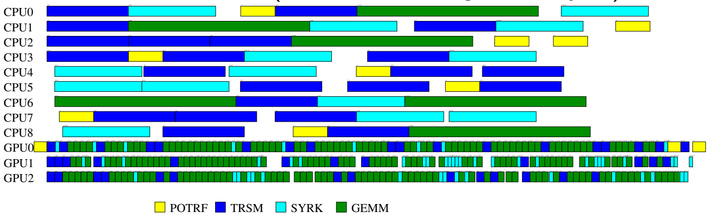
- Heterogeneous settings
  - Hexacore Westmere Intel Xeon X5650 processors (12 CPU cores per node): **9 CPU cores** since 3 are dedicated to data transfers
  - **3** Nvidia Tesla M2070 **GPUs**

POTRF	TRSM	SYRK	GEMM
$\simeq 2.3\times$	$\simeq 11\times$	$\simeq 26\times$	$\simeq 29\times$

Table : GPUs relative performance

Achievable Solutions, $n = 12$

- Best Known Solution (Constraint Prog., 15 days !): 785 GFlops



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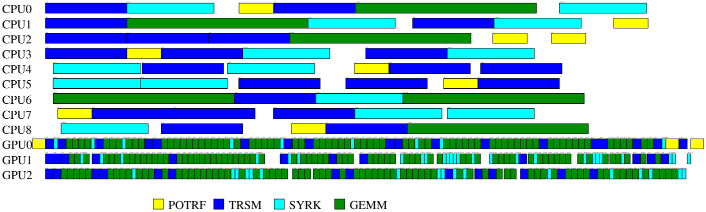

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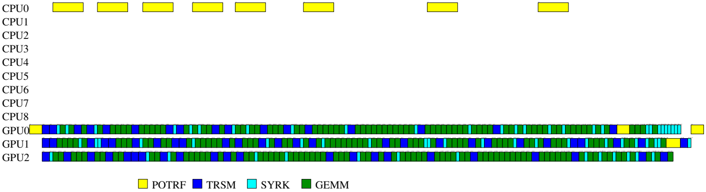
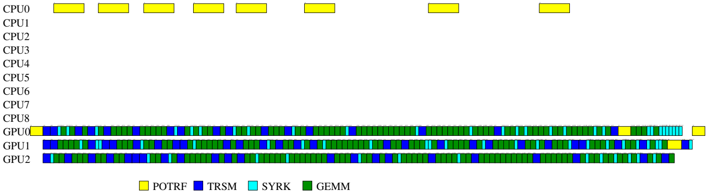


- very disappointing...
  but enough to achieve pseudo-super-linear speedup !

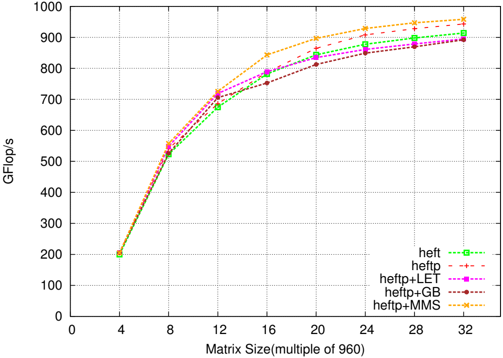
Outline

Improving StarPU scheduler (I) [IPDPS'16, S. Kumar]



- StarPU is too cautious
  - It fails to allocate enough tasks on a CPU
  - even though it would not have induced idle time on a GPU
- Improvement over default policy
  - Pseudo-Allocate next task on CPU
    - Simulate StarPU until the ending time of the task
    - using SimGRID simulator
  - Reallocate on a GPU iff it induces idle time on GPU
- and several variants.

Improving StarPU scheduler (II)



- Variants: how far is it worth to simulate ?
- for $n = 12$, $680 \rightarrow 725$ (best 785)
- much more expensive than default policy, but
    - Dedicate one CPU to compute the schedule !

Acceleration Ratio-based Policies (I)

POTRF	TRSM	SYRK	GEMM
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- GPUs should prefer GEMMs to SYRKs to TRSMs to POTRFs
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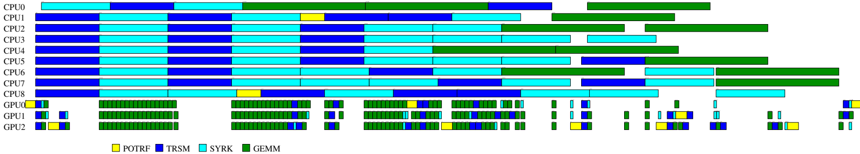

- works poorly :440 Gflops vs Best 785 GFlops:
  GPUs wait for tasks performed by CPUs

Acceleration Ratio-based Policies (II)

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- merge some queues + allow task spoliation (if GPU gets idle)

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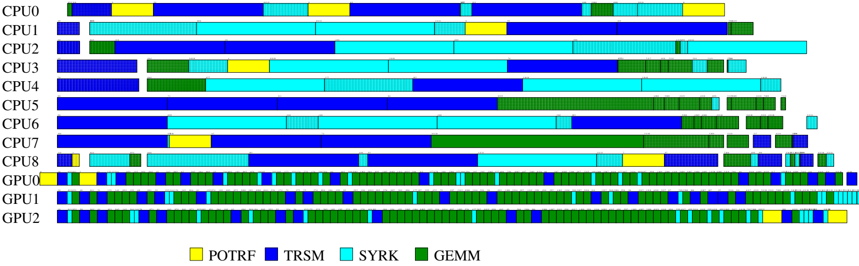

- works fine: 750 (best known solution is 785)

Outline

Static vs Dynamic Strategies

- To do a fair comparison, let us add uncertainties
- task completion times belong to $[90\%, 110\%] \times$ expected time
- In Static Schedules, allow GPUs to perform spoliation
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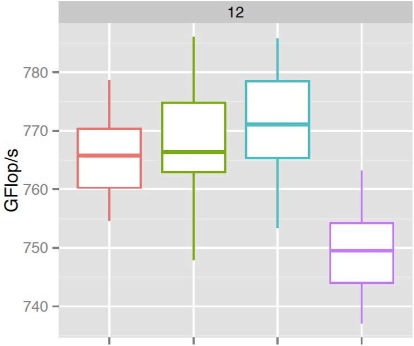
- And the winner is: **Static Again !**



- red: Pure Static
- green: Hybrid (Static + GEMM Spoliation)
- cyan: Hybrid (Static + GEMM-SYRK Spoliation)
- purple: Best Dynamic

Outline

Static or Dynamic ?

- First Conclusions
  - Dynamic Schedulers achieve good results
  - They are able to use both fast and slow resources
- Static Schedules are (expected to be) bad since they are
  - Hard to compute
  - Likely to perform badly under uncertainties
- But...

Dynamic Schedulers are far from the optimal

- MapReduce and Non Local Map Tasks
  - Hadoop: replicates to improve locality
    - greedily allocate tasks to resources
    - induces comms (highly depends on settings, was 10%)
  - Static policy:
    - solution of a $b-$matching problem, almost no comms
- Matrix-Multiplication and data transfers
  - StarPU: puts tasks resources that already hold input data
    - $2.5\times$ the lower bound
  - Static policy: based on an initial partitioning of the matrices
    - NP-Complete but 1.15 worst case and on av. 1.05 the LB
- Cholesky and Heterogeneous Unrelated Resources
  - StarPU: Allocate on a CPU if it ends faster than on GPUs
    - with $n = 12$, 680 GFlops (still better GPUs only)
  - Static: Schedule based on Brute Force Constraint Prog.
    - Hard Optimization Problem but 785 GFlops (even with noise)

Injecting Static Knowledge into Dynamic Schedulers

- MapReduce and Non Local Map Tasks
  - Use Static Optimal Solution to find local preferred tasks
  - $\rightarrow$ works well even with non homogeneous tasks
- Matrix-Multiplication and data transfers
  - StarPU policy: $\rightarrow 2.5\times$ the lower bound
  - Analyze the fluid relaxation of the system $\rightarrow 2\times$ LB
  - Best Static $\rightarrow 1.05\times$ LB
- Cholesky Factorization: Heterogeneous Unrelated Resources
  - StarPU policy $\rightarrow$ 680 GFlops
  - Use Simulation to have a less myopic policy $\rightarrow$ 725 GFlops
  - Use Knowledge of Cholesky to define affinities $\rightarrow$ 760 GFlops
  - Hard Combinatorial Optimization Problem $\rightarrow$ 785 GFlops

Injecting Dynamism into Static Policies

- MapReduce and Non Local Map Tasks
  - Replication enables to cope with uncertainties in execution times
- Matrix-Multiplication and data transfers
  - If processing times fluctuate
    - Start with Static then Use Work Stealing
    - $1.05 \rightarrow 1.5\times$ (for extreme & unrealistic variations)
  - still better than the 2.5 or even 2
- Cholesky Factorization: Heterogeneous Unrelated Resources
  - If processing time Fluctuate
    - Keep the same allocation + ordering of tasks
    - except if GPUs get idle and CPUs perform GEMMs $785 \rightarrow 770$ GFlops
    - still better than 760 GFlops

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- Still many things to do
  - Three simple kernels only
  - but we tried our best in all directions !
- There is plenty of room
  - Work on Optimization Problems for specific applications
  - Inject Knowledge of the Application into Dynamic Schedulers

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Thank You ! Mail to {Olivier.Beaumont@inria.fr}

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