Coopération en Informatique Parallèle

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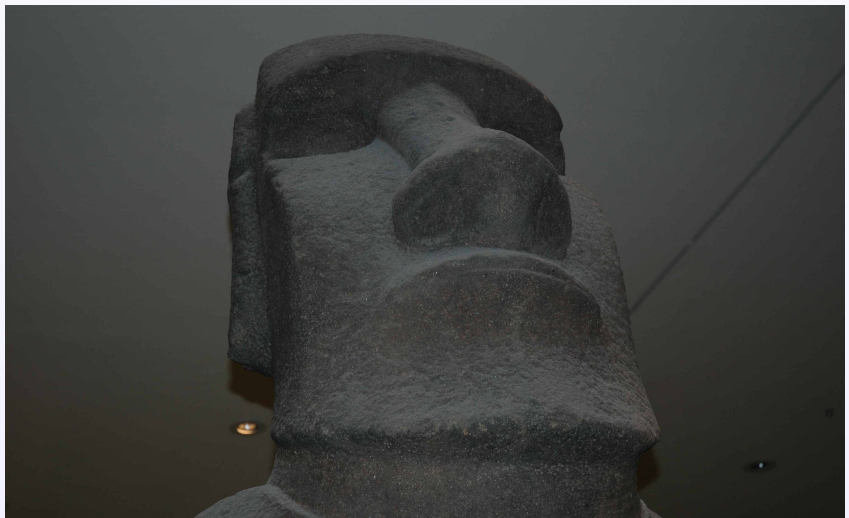

Outline

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Parallel everywhere

Informally, **parallelism** is the simultaneous use of multiple computing devices (whatever they are).
Today. (Example of molecular dynamics):

- The codes are multi-scale (classical dynamic and quantum chemistry).
- Several hundreds of thousands atoms.
- Sophisticated visualization modules.
- In Situ simulations (adaptive).

HPC (High Performance Computing)

TOP500: an international organization created in 1993.
Website updated twice a year.

Main goal: to rank the most powerful computing platforms.
Historical data, stats, evolution tendencies (energy, accelerators),
...

Petit intermède culturel...

Performance scale: 10^3

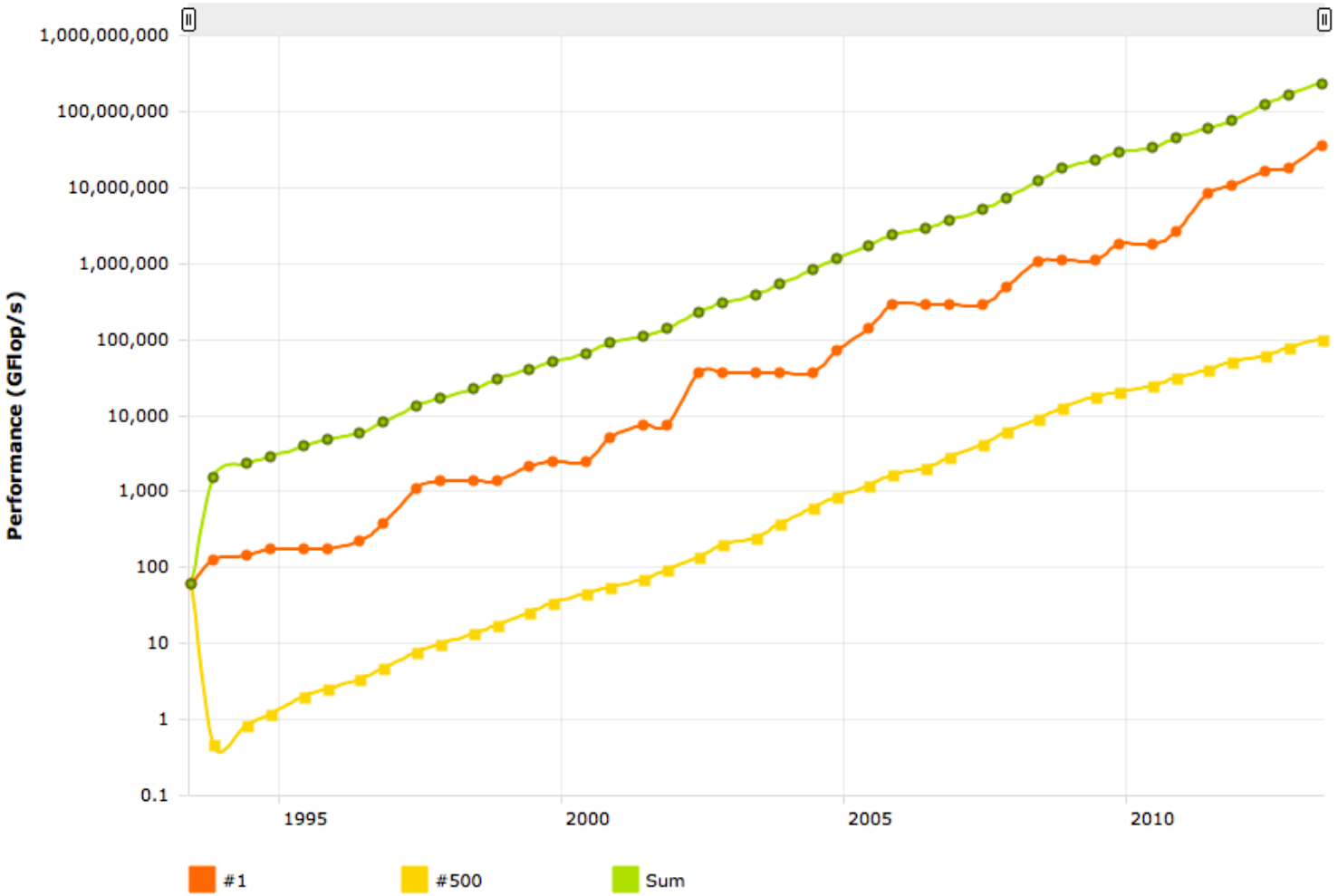
- Mega
- Giga (Giant)
- Tera (monster)
- Peta
- Exa
- ...

Evolution of computing: The TOP'500

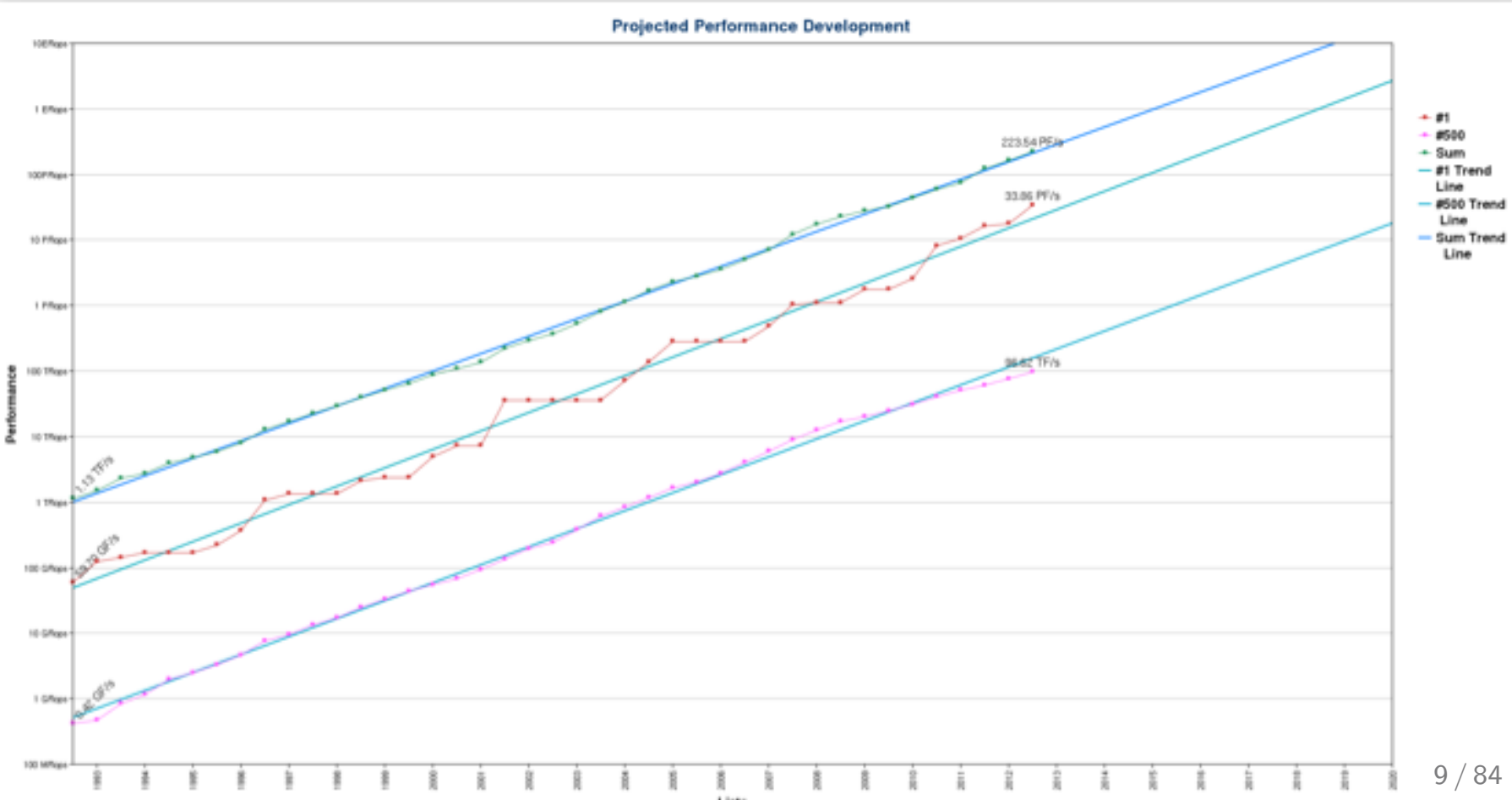
http://www.top500.org/statistics/perfdevel/
maximum performance (in PetaFlops) and efficiency (average on peak)

- Tianhe-2 Milky Way-2 (China) – 33.86
- Titan (Cray - USA) – 17.59
- Sequoia (IBM - USA) – 17.17
- K-computer (Fujitsu, Japan) – 10. 51

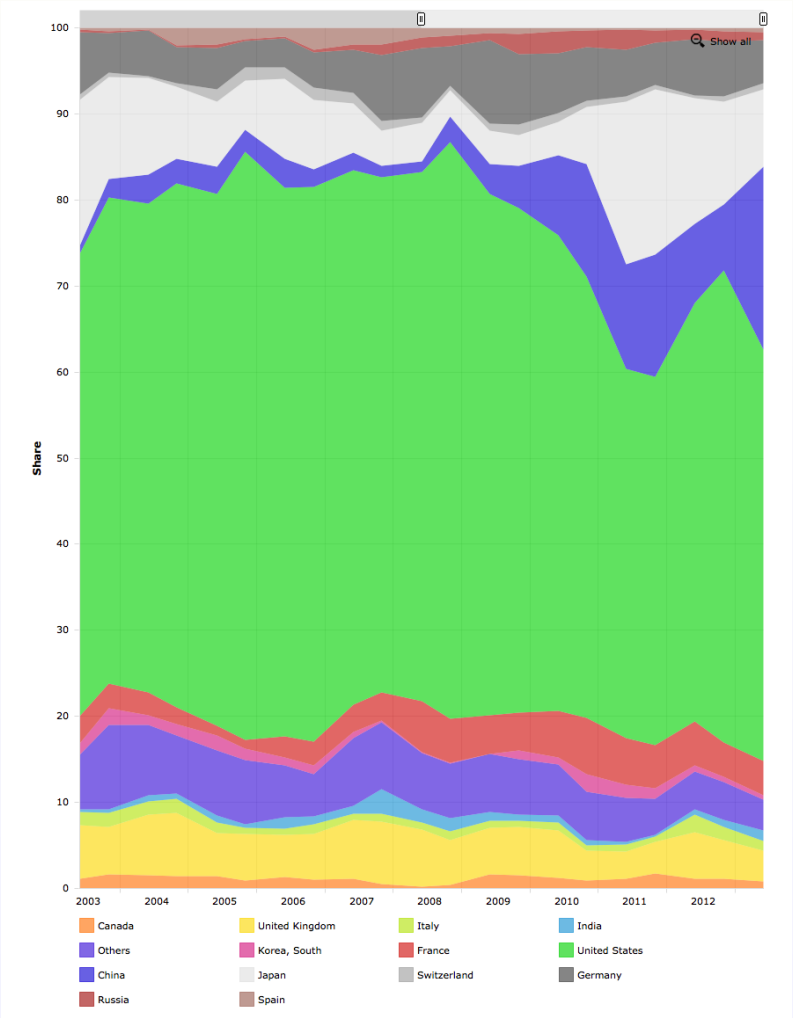
Evolution during these last 20 years



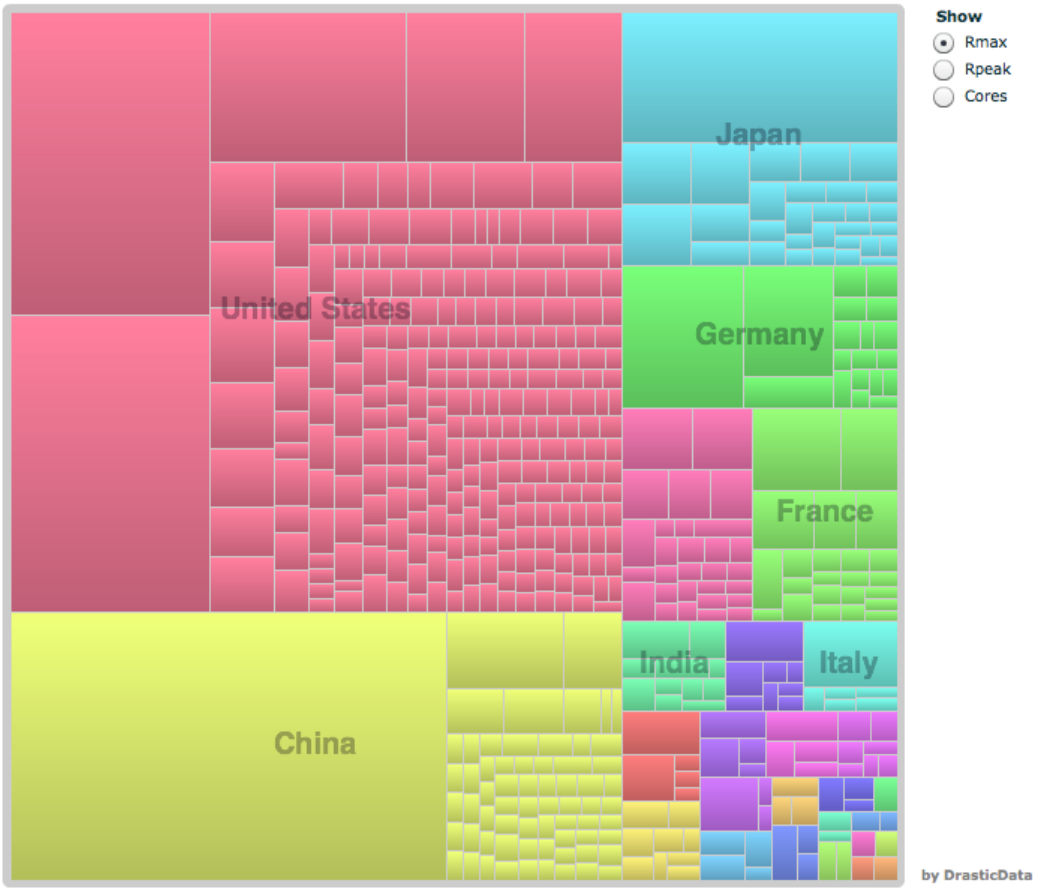
Predictions for the next years



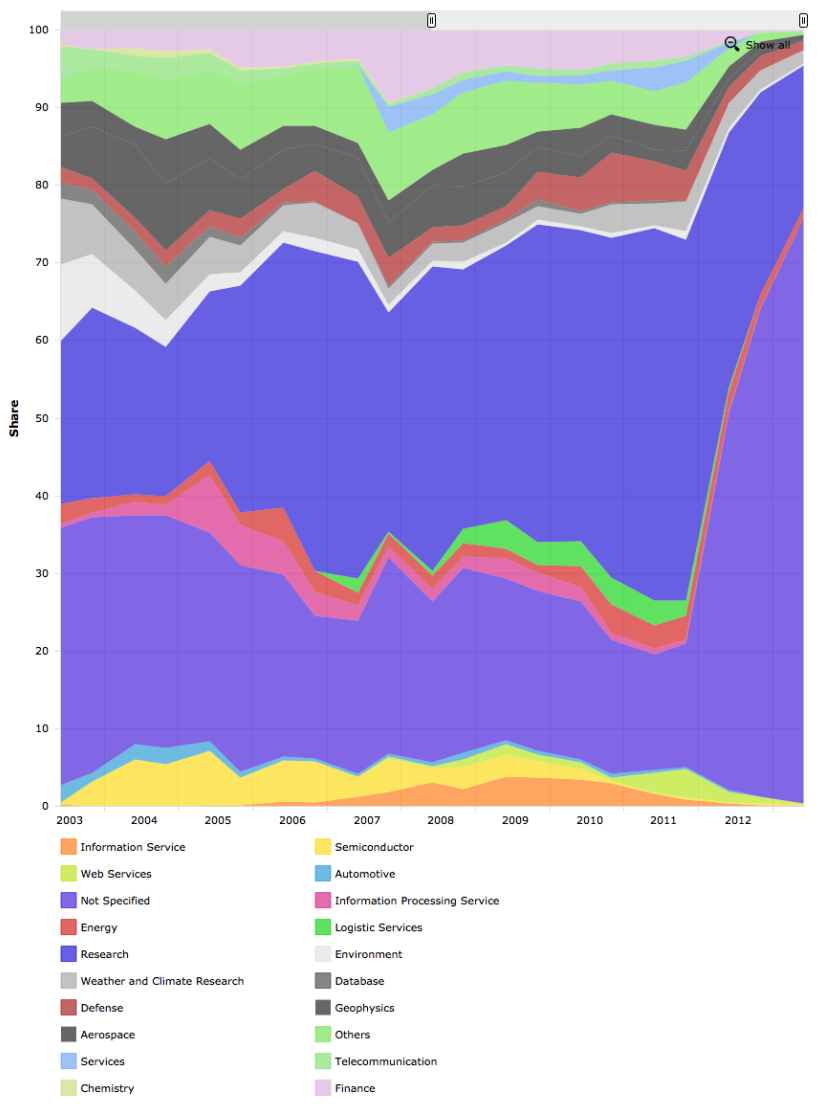
A deeper look: evolution by countries



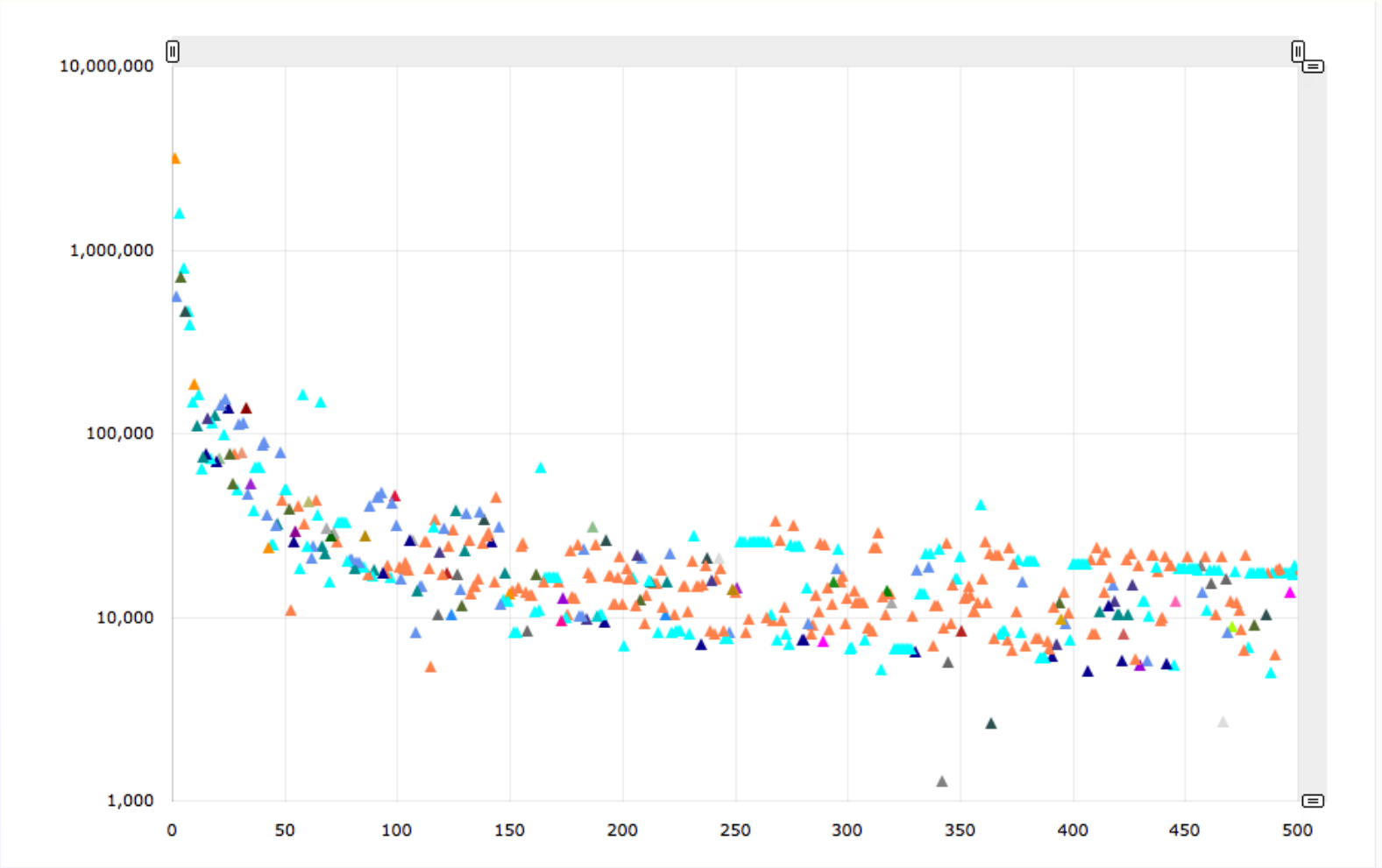
A deeper look at the countries in 2013



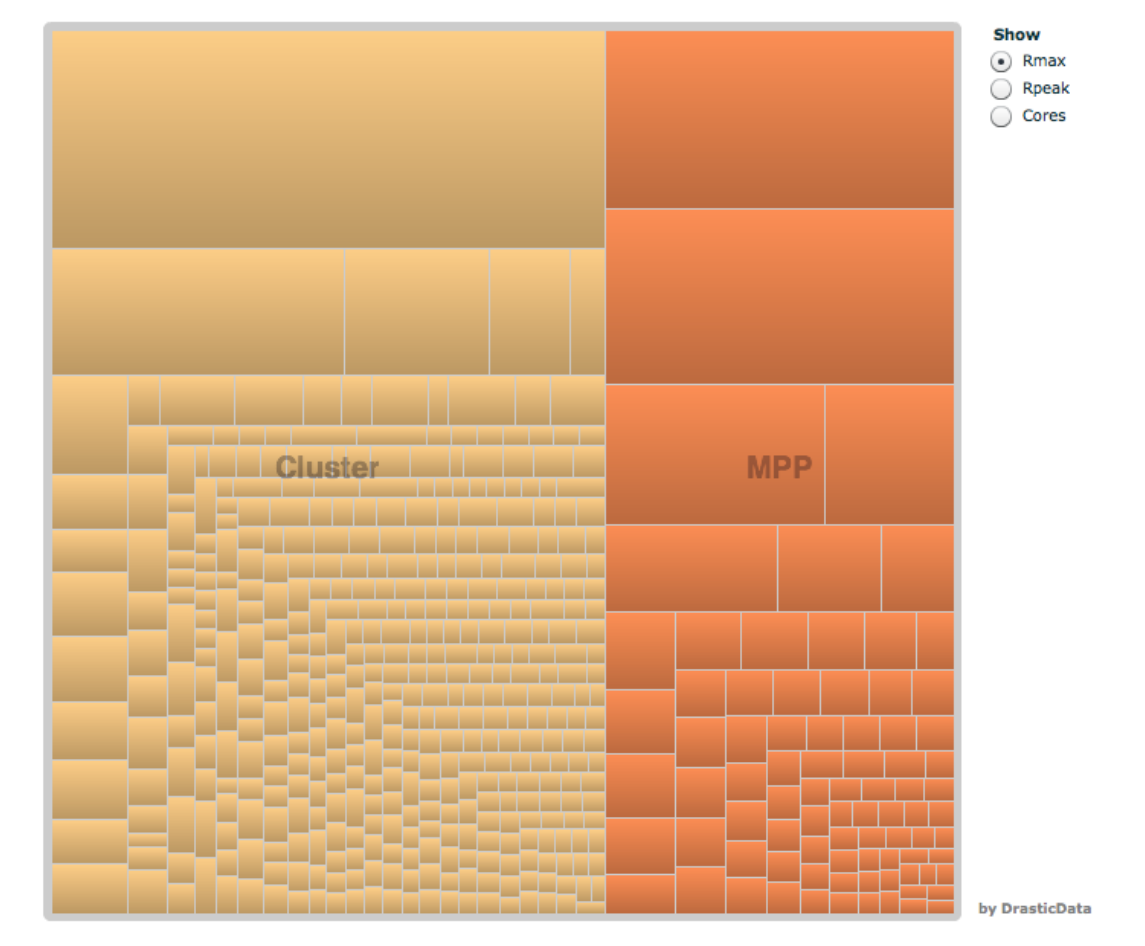
Repartition of the running applications



Number of cores



Type of architectures



Order of magnitude

Comparison with today computing platforms in term of maximal performances (in GigaFlops).
In the TOP'500 from 1993, the most powerful machine reached 59 GigaFlops.
20 years later, the basic processors are more powerful (the Galaxy – or Iphone – under Android are not too far!).

The computing landscape today...

New and future high performance computing platforms

- Computational grids
- Desktop grids (volunteer computing)
- Hybrid multi- and many- cores (accelerators)
- Clouds

Common characteristics in all kind of most platforms

- Very large number of resources
- Distributed features (hierarchical structure)
- Heterogeneity (with accelerators)
- Uncertainties on data at any level
- Energy limitations

The challenge today is on the **automation and universality** of software (and tuning) tools

Emergence of new parallel platforms

The evolution of high-performance execution platforms leads to physical or logical distributed entities (called **organizations**) which have their own local rules. For instance, CiGri platform in Grenoble. Each organization is composed of multiple users who compete for the resources, and they aim at optimizing their own objectives. Such systems are often hierarchical (many-core).

Proposal:

To create a general framework for studying the resource allocation problem for most situations and study in this context the concept of **cooperation**.

Multi-organization scheduling

Informally, a set of users have some applications to execute on distributed resources. These resources belong potentially to multiple organizations that may have their local control and rules. The objectives of the users are not necessarily the same, but they are related to a metric on the completion times (i.e. the finishing times) of the jobs.

Synthetic view of the problem

More formally

The problem is to allocate the jobs to the available resources according of a certain objective. Then, the jobs are scheduled locally.

The set of jobs is available at time 0, the execution is performed by a series of successive time frames (called batches).

Formally

The parallel platforms are viewed as entities which have all their local rules. Each physical entity is composed of users who compete for resources with their own needs or wishes.

Generic problem

to allocate *jobs* to available computing (or networking) distributed resources aiming at optimizing some objective.
Then, execute them locally.

We have to determine **when** and **where** to execute the jobs. This corresponds to two interleaved problems, namely π (allocation) and σ (scheduling).

Some notations

- m "machines"
- n jobs de duration p_j for $1 \leq j \leq n$ (sometimes the jobs are them-selves parallel applications)
- N users, owning each n_i jobs

Practically (in existing systems), several priority queues which manage the jobs according to some policy (FCFS and its variants like *back filling*).

Problems classification

Key parameters

- **Users**
- **Applications (jobs)**
- **Resources**
- **Control**
- **Objective(s)**

Methodology for the analysis

- Modelization and formal definition of the problem
- Complexity analysis (NP-completeness, inapproximation)
- Algorithms design
- Analysis (worst case bounds, simulations, realistic testbeds)

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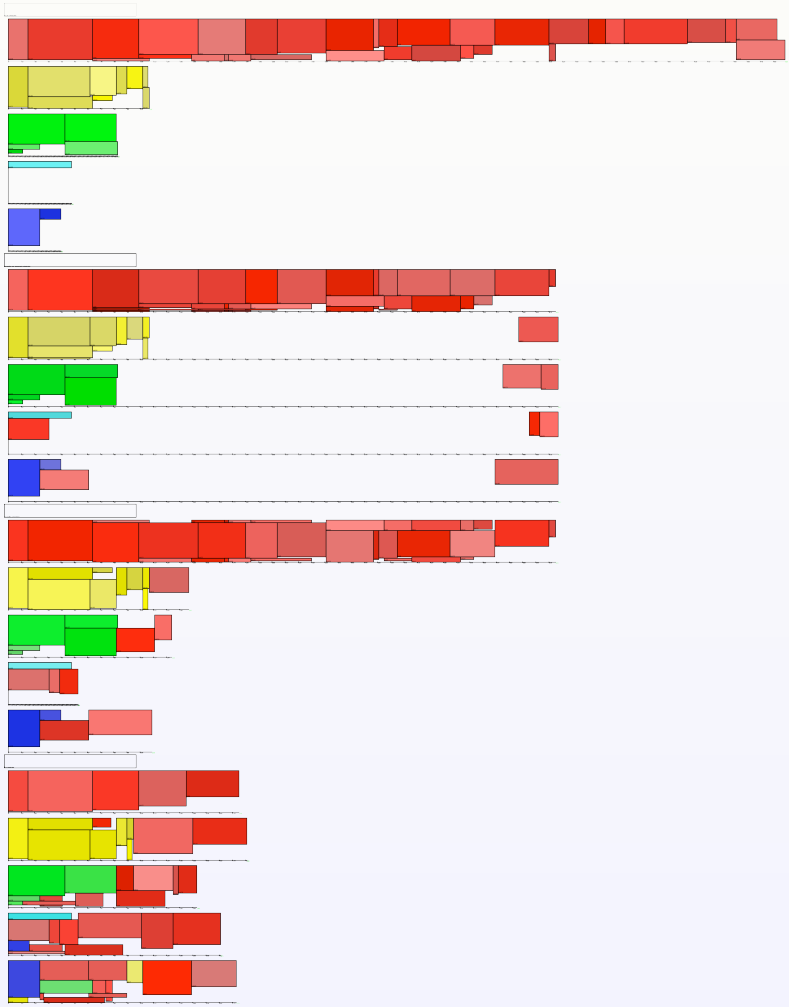
The idea is to study various problems with the same way (and create adequate common tools).

Brief recall on complexity

We distinguish between easy problem (those for which there exists polynomial algorithms) and hard problems. These problems are characterized by their ability to check if a solution is valid (in polynomial time).
We do not expect exact solutions for big instances, thus, we are looking for approximation algorithms running in reasonable times.

Example



Outline

Starting smoothly with well-known results

A preliminary basic problem

- **Users:** **single** or multiple, uniform or heterogeneous
- **Jobs:** **sequential**, parallel (rigid or malleable), divisible loads
- **Resources:** single, **identical** , hierarchical, heterogeneous
- **Control:** **centralized** or distributed
- **Objectives:** **Cmax**, $\sum C_i$, stretch

Classical $P||Cmax$ problem

Informally, this corresponds to the situation of a single (homogeneous) cluster.
Scheduling n independent jobs on m arbitrary parallel identical processors aiming at minimizing Cmax.

Complexity:

The problem is weakly NP-hard [Ullman'75].

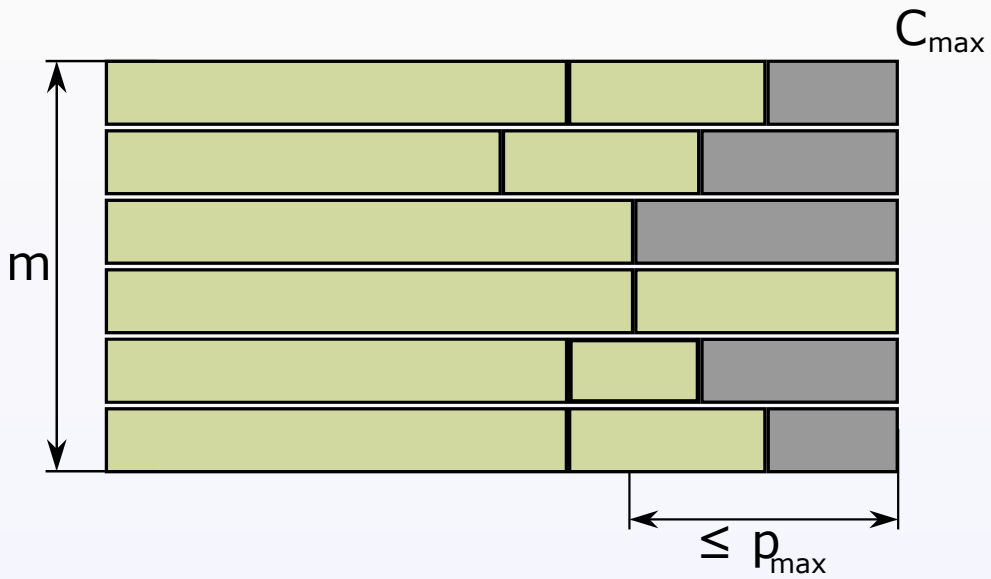
Solving by a list algorithm

Algorithm framework:
List-scheduling [Graham'69] (greedy) whose principle is to build a list of ready jobs, and to execute any of these jobs as soon there are available processors. This algorithm has a guarantee in the worst case.

Remarks:
(asymptotically) optimal algorithm for a large number of jobs.

Analysis 1

The idea is based on a geometrical proof on the Gantt chart:



$m.Cmax = W + S_{idle}$ (where $W = \Sigma_j p_j$)

Analysis 2

Proposition.

List scheduling is a 2-approximation.

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Lower bounds:
$Cmax^* \geq \frac{W}{m}$ and $Cmax^* \geq p_{max}$

Analysis 2

Proposition.

List scheduling is a 2-approximation.

$m.Cmax = W + S_{idle}$

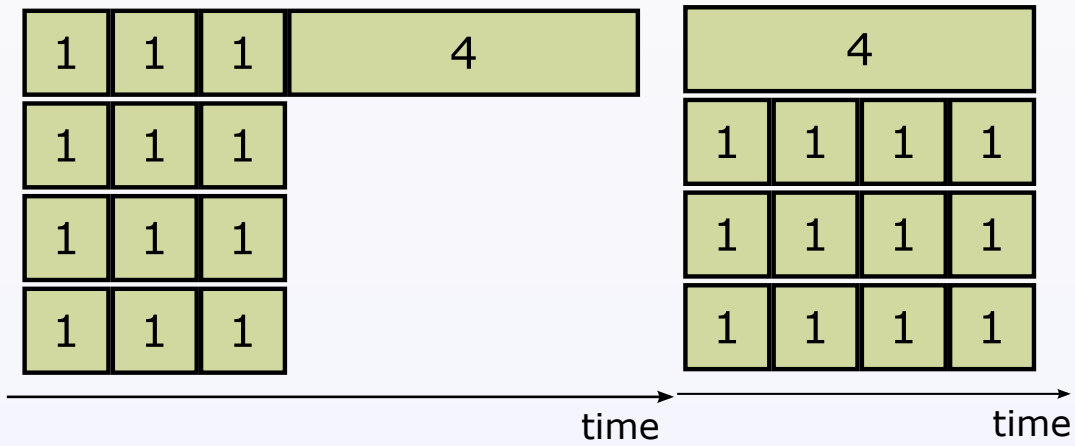
Lower bounds:
$Cmax^* \geq \frac{W}{m}$ and $Cmax^* \geq p_{max}$

$S_{idle} \leq (m-1).p_{max} \leq (m-1).Cmax^*$
$Cmax = \frac{W}{m} + \frac{S_{idle}}{m} \leq (1 + \frac{m-1}{m}).Cmax^*$

Tightness for general list scheduling

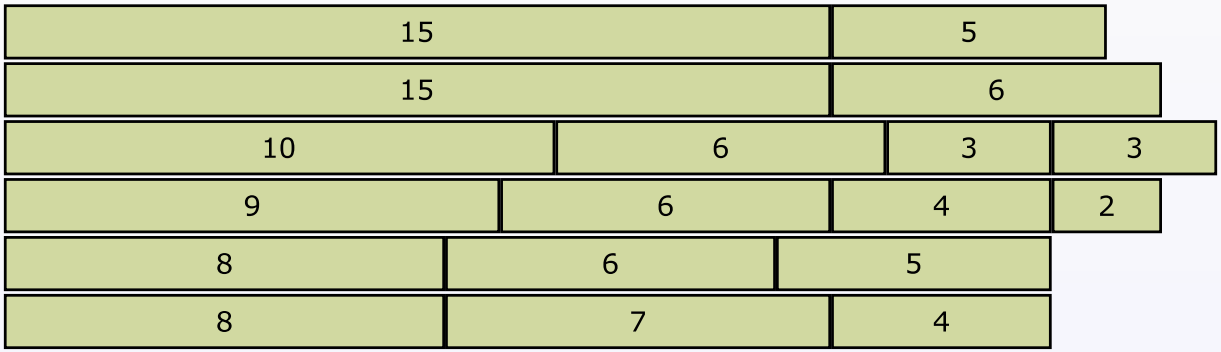
Proposition.

The worst case bound of $2 - \frac{1}{m}$ for list scheduling is tight.



improvement: the LPT rule

Based on the tightness of the 2-approximation ratio, the bound can be improved by considering the specific LPT policy (largest processing times first):



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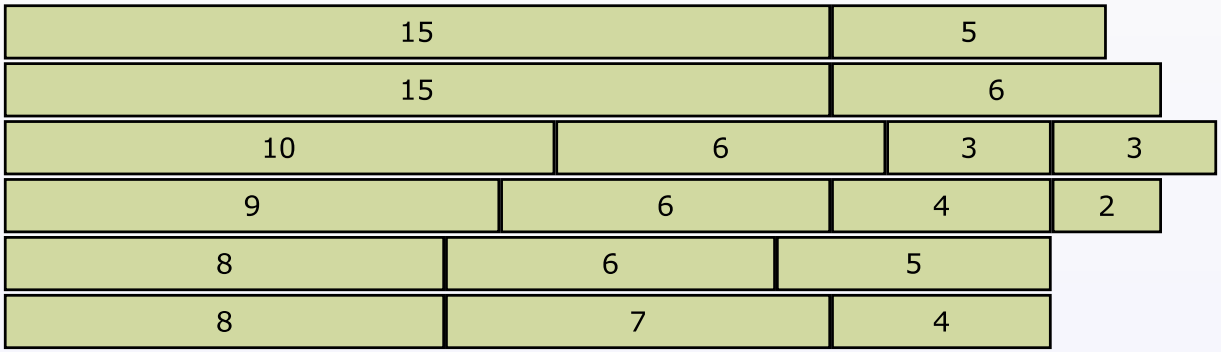
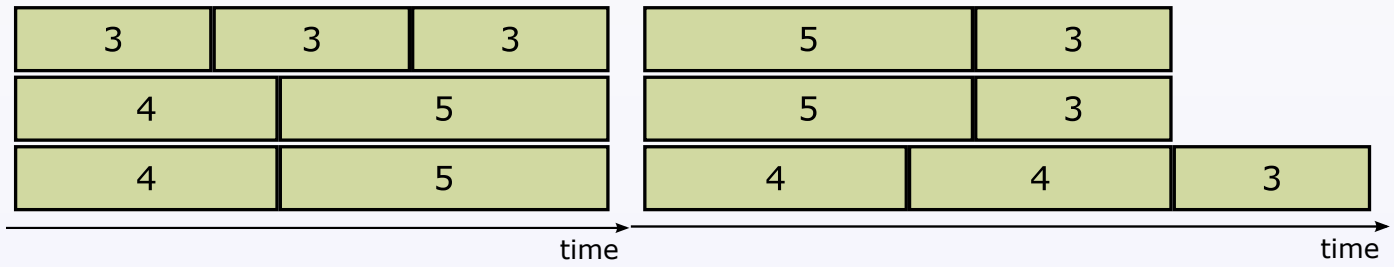


Approximation bound: $\frac{4}{3}$ (for $m \geq 2$)

Tightness of LPT

Proposition.

The worst case bound of $\frac{4}{3} - \frac{1}{3m}$ for LPT is tight.



Synthesis

List is a very nice framework which realizes a good trade-off between simplicity and efficiency.
It can be extended to many cases, sometimes it is possible to analyze theoretically.

- other objectives ($\sum C_i$ with the "reverse" SPT policy which is optimal for n independent jobs on m machines)
- taking into account communication costs
- Parallel rigid jobs

Outline

Problem

- **Users:** **single** or multiple, uniform or heterogeneous
- **Type of applications:** sequential, **parallel rigid** or malleable, divisible loads
- **Resources:** single, **identical**, hierarchical, heterogeneous
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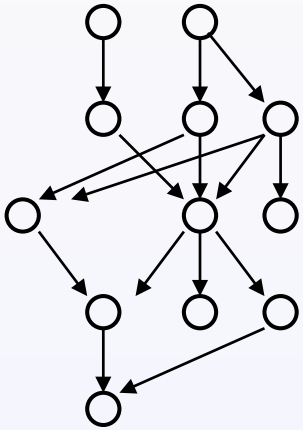
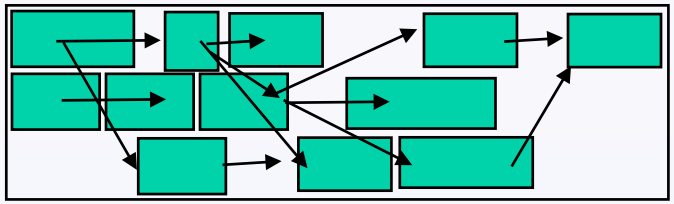
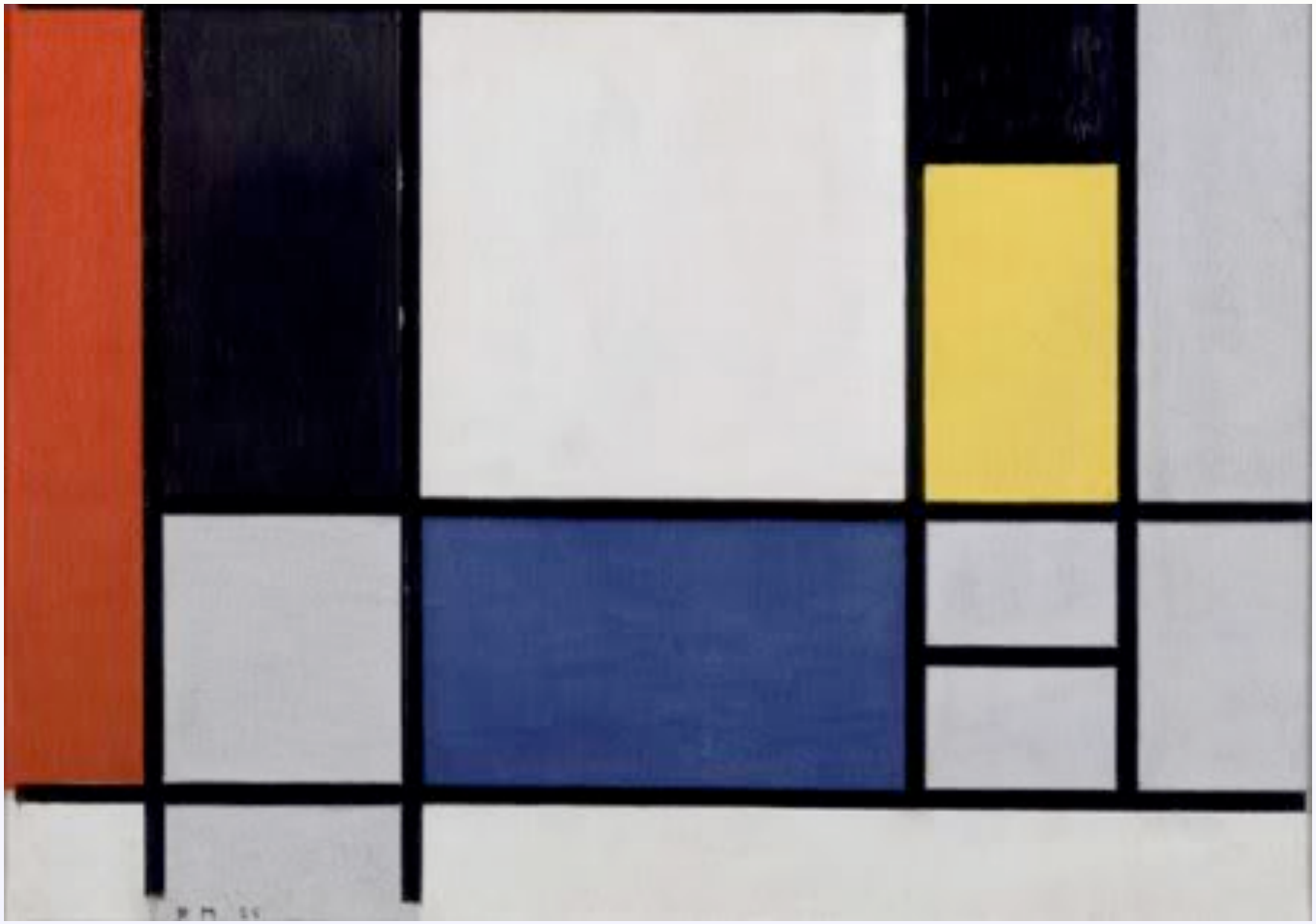
Rigid jobs

Rigid jobs correspond to parallel applications



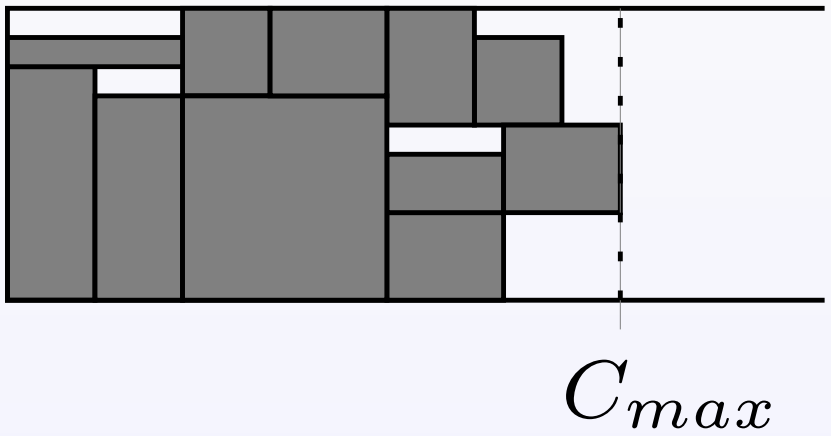




Problem statement

Problem:

Given n independent rigid jobs to be scheduled on one cluster composed of m identical machines minimizing the makespan $Cmax$.



Complexity results for one strip

The problem is obviously NP-hard.

Complexity results for one strip

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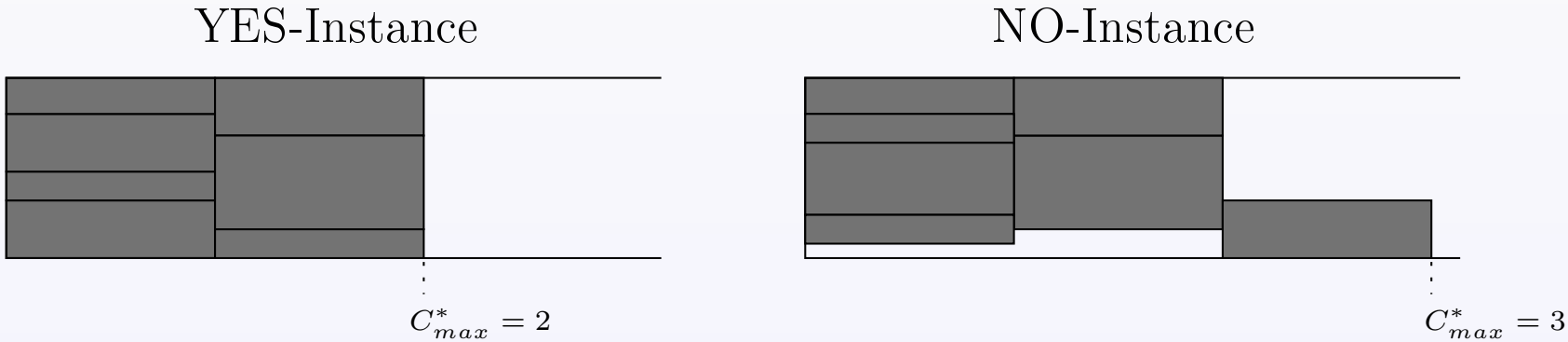
It is $\frac{3}{2}$-inapproximable unless $P = NP$



Algorithms for one strip

- List Scheduling is still a $(2 - \frac{1}{m})$-approximation for non continuous case only! Introduced by Graham in 1975 and revisited recently by Eyraud, Mounié and Trystram in IPDPS 2007.
- Steinberg/Schiermeyer: fast 2-approx available for both versions
- Jansen: very costly $(\frac{3}{2} + \epsilon)$-approx available for both versions
- Kenyon-Remila: *AsymptoticFPTAS* available for both versions

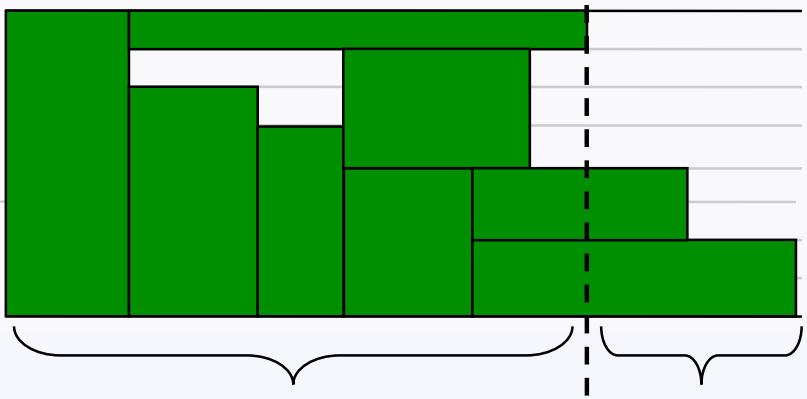
Including extra rules

HF (Higest first) is a natural extension (similar to the LPT rule).

Bad news: no better approximation as for general list (open question)
Good news: nice dominance rule

Analysis of HF policy

HF (Highest first) is a list algorithm that sorts the jobs by non-increasing order of their height.

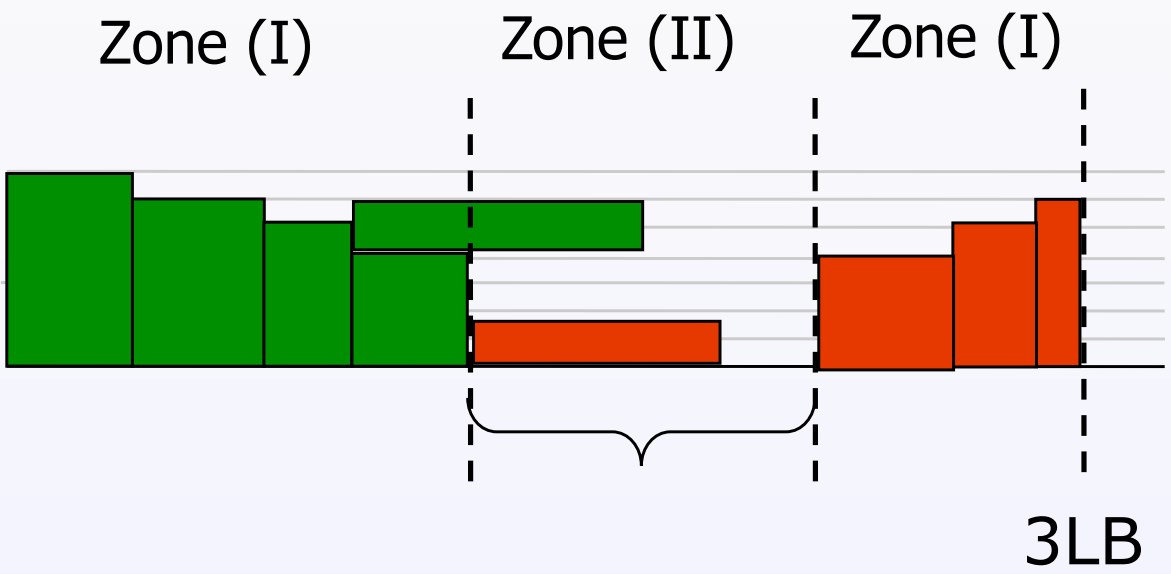


high utilization zone (I)
(more than 50% of processors are busy)

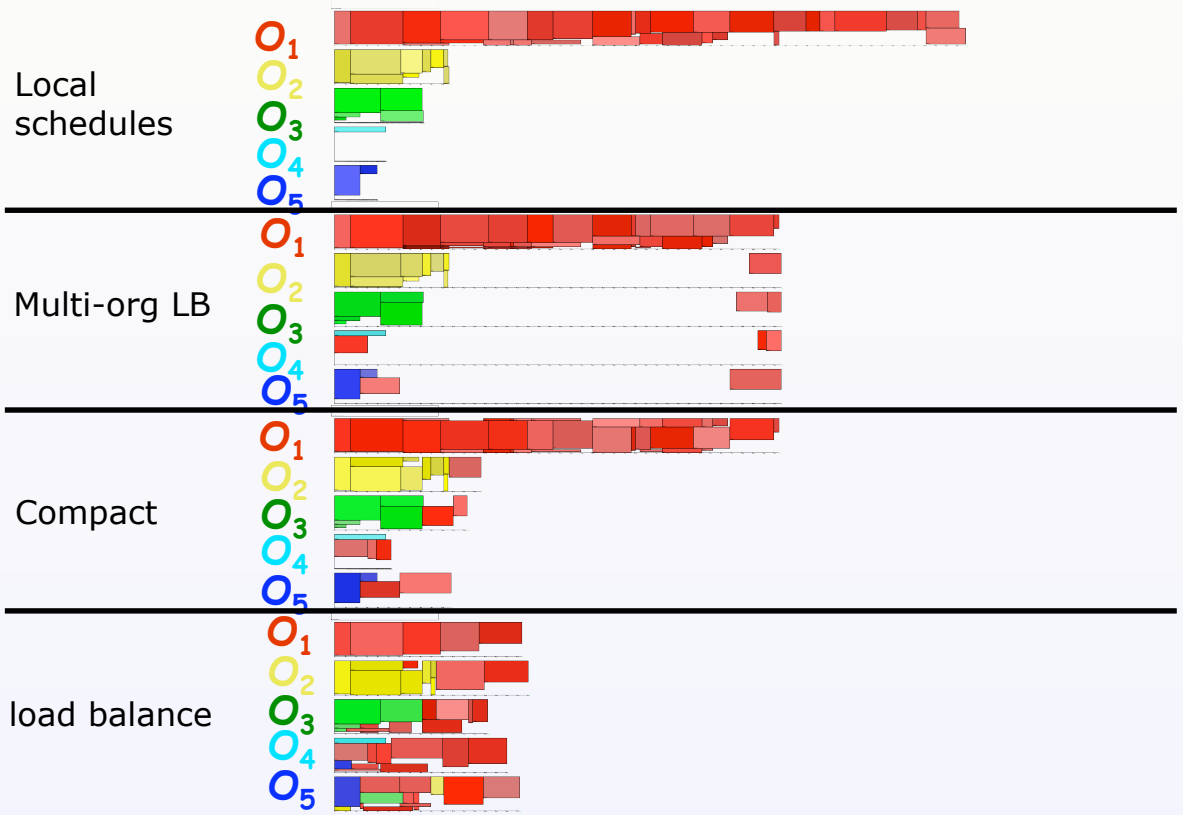
Approximation algorithm - analysis

Proposition.

The previous algorithm is a 3-approximation even for irregular strip sizes.



Analysis of HF policy



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Problem

- **Users:** **single** or multiple, uniform or heterogeneous
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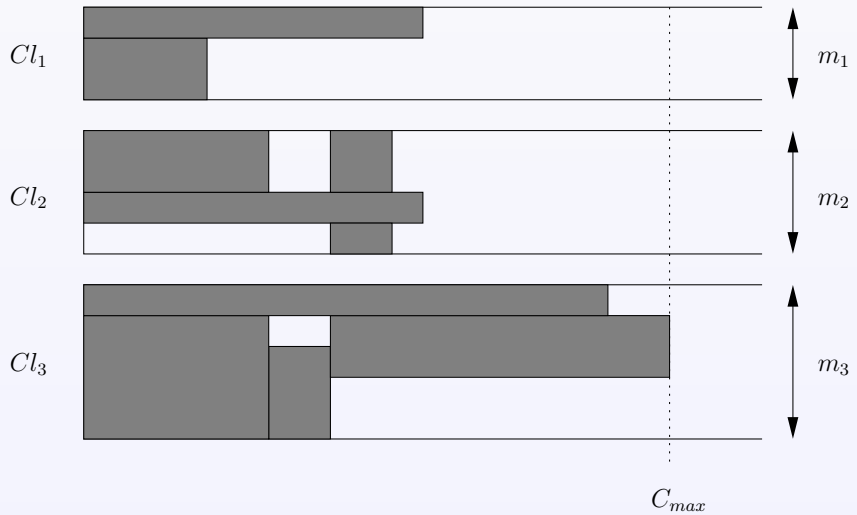
Scheduling rigid parallel jobs

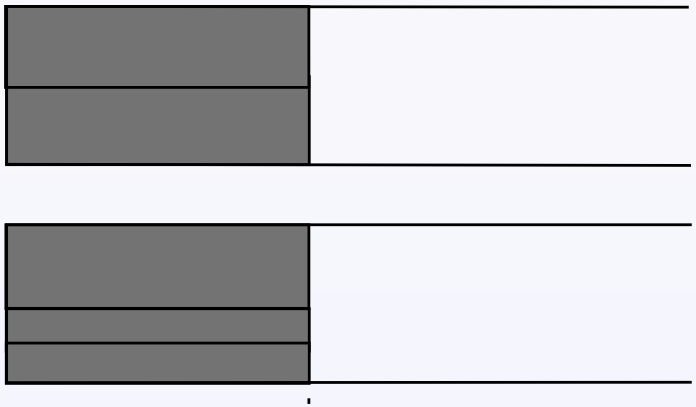
- **Problem:** Given n independent rigid tasks and k cluster (cluster Cl_i owns m_i machines), schedule all the jobs minimizing the makespan C_{max}.
- The continuous Vs non continuous discussion still holds..



Negative result for Multi-Strip

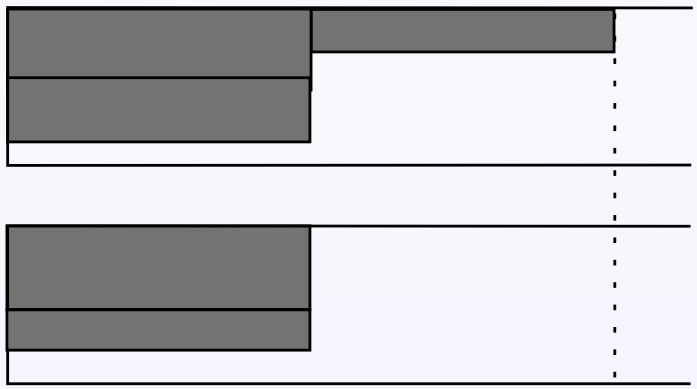
- multi-SP are 2-innapproximable unless $P = NP$, even for $k = 2$ strips

YES-Instance



$C^*_{max} = 1$

NO-Instance



$C^*_{max} = 2$

Toward positive results for multiSP

- How getting a $\frac{5}{2}$ ratio for regular multiSP?

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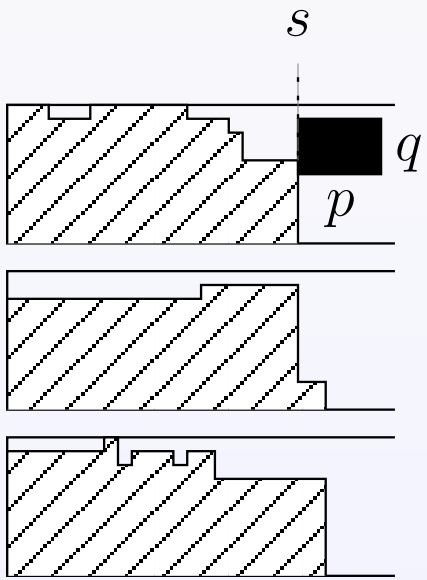
- How getting a $\frac{5}{2}$ ratio for regular multiSP?
- Using LS again: consider the last finishing task (of size (p, q)) starting at time s



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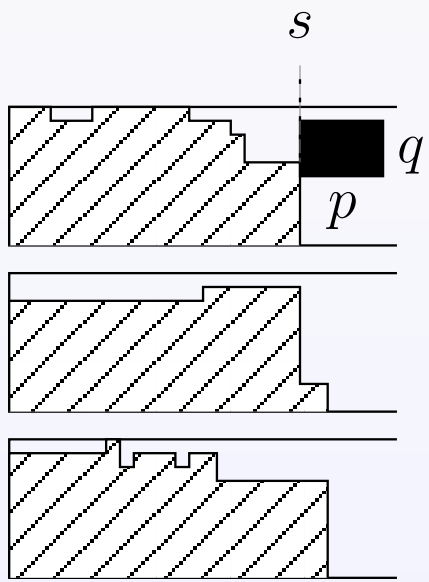
$$
\begin{aligned}
W &\geq ks(m-q) \text{and thus} \\
C_{max} &= s + p \\
&\leq \frac{W}{k(m-q)} + p \\
&\leq \frac{m}{(m-q)\frac{W}{km} + p} \\
&\leq C^*_{max}\left(\frac{m}{m-q} + 1\right)
\end{aligned}
$$



Toward positive results for multiSP

- How getting a $\frac{5}{2}$ ratio for regular multiSP?
- Using LS again: consider the last finishing task (of size (p, q)) starting at time s
- Thus we need small values of p and q

$$
\begin{aligned}
W &\geq ks(m-q) \text{and thus} \\
C_{max} &= s + p \\
&\leq \frac{W}{k(m-q)} + p \\
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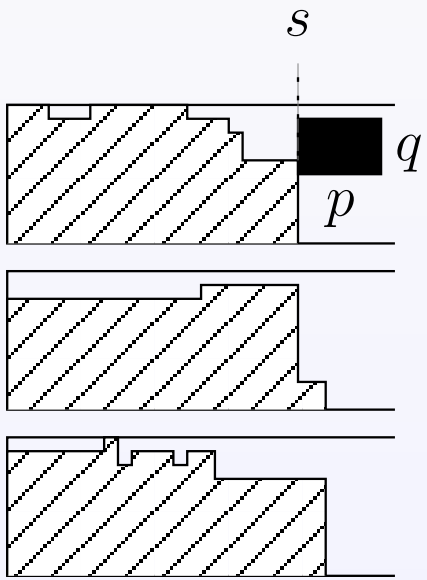

Toward positive results for HSP

- We want (for example) $p \leq \frac{C^*_{max}}{2}$ and $q \leq \frac{m}{2}$, directly leading to a $\frac{5}{2}$ ratio.

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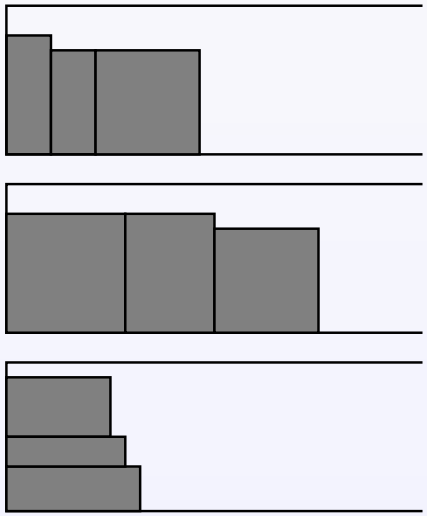
- Thus, we first schedule carefully all jobs having $p > \frac{C^*_{max}}{2}$ or $q > \frac{m}{2}$ using simple structures like shelves and layers.



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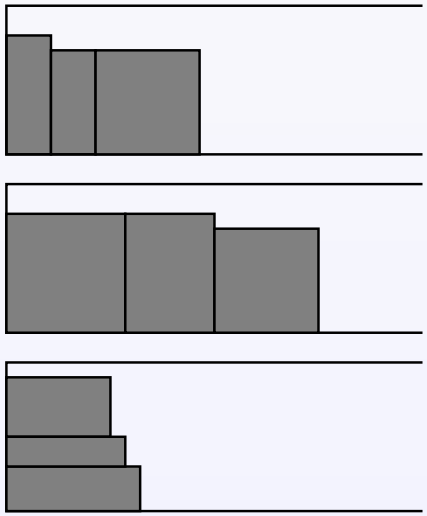
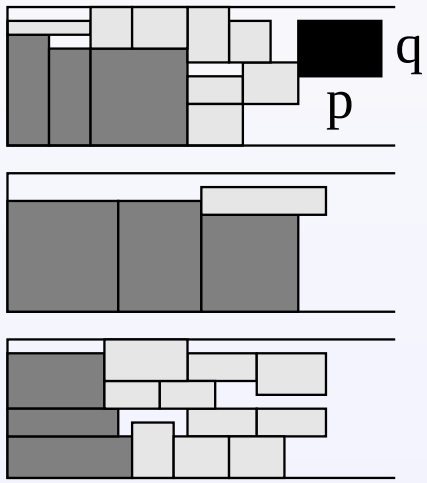
- Thus, we first schedule carefully all jobs having $p > \frac{C^*_{max}}{2}$ or $q > \frac{m}{2}$ using simple structures like shelves and layers.
- Then, we add using LS the small remaining jobs





Outline

Add local constraints

- **Users:** **single** or multiple, uniform or heterogeneous
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Motivations

In the last results, different *organizations* shared processors and exchange jobs in order to maximize the profits of the whole community.

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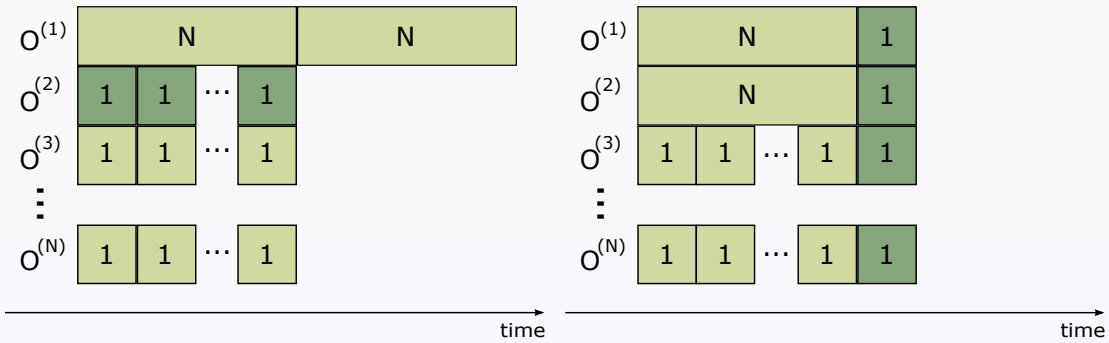
Locally, an organization can act *selfishly* and refuse to cooperate if in the final schedule one of its (migrated) jobs could be executed earlier in one of its own processors.
The focus here is to study the impact on the global performance ($Cmax$) of cooperation between selfish organizations. The local objectives are to minimize local $Cmax$.

Notation:
MOSP($Cmax$).

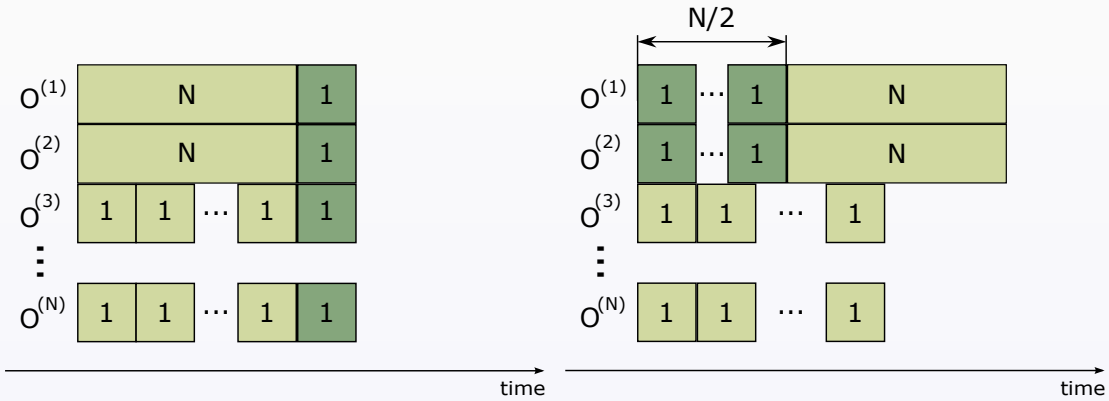
MOSP constraints



(a) Initial instance

(b) Global optimum without constraints

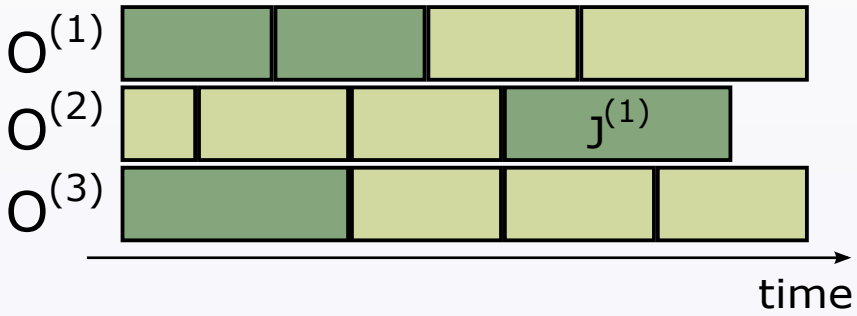
MOSP constraints



(c) Global optimum without constraints

(d) Optimum with local constraints

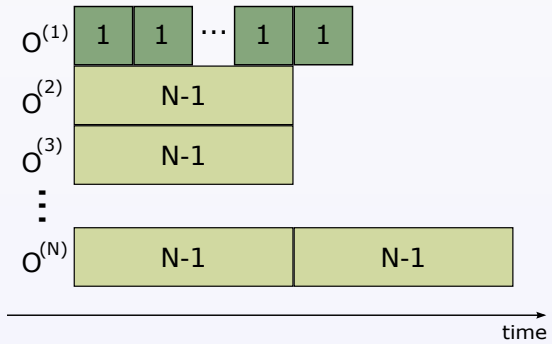
Selfishness restrictions 1



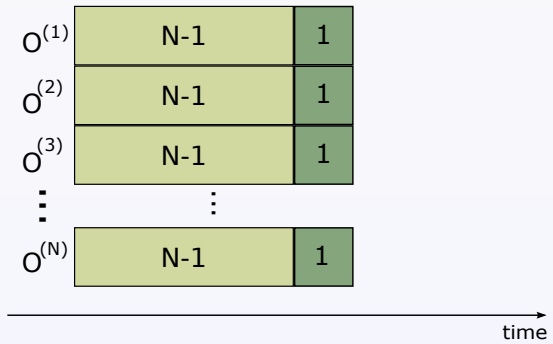
Selfishness restrictions 2

Inapproximation.

MOSP($Cmax$) is strongly NP-complete.
Ratio between approximation algorithms with and without selfishness restrictions: $\geq 2 - \frac{2}{N}$



(e) Optimal with selfishness restrictions



(f) Optimal with local constraints

Approximation algorithms

The idea is (again) to use LPT for solving MOSP with selfish restrictions.

Phase 1: If solving MOSP($Cmax$), each organization applies LPT locally for its own jobs.

Phase 2: Global LPT: each time an organization becomes idle, the longest job that does not have started yet is migrated and executed by the idle organization.

Analysis

Proposition:

MOSP is a 2-approximation.

Proof.

- Phase 2 works as a list scheduling, so Graham's classical approximation ratio $2 - \frac{1}{N}$ holds for all of them.
- It is feasible since the migrated jobs are always executed earlier than the original schedule; this guarantees that the *selfishness restriction is always respected* and that both *Cmax* of the original organization is not increased;

Outline

Model of multi-organization scheduling

- *organizations* $O^{(u)}$ have *resources* (clusters) and some *local jobs* $\{J_i^{(u)}\}$
- system goal: global makespan $C_{\max}$
- each organization minimizes the makespan of its local jobs $C_{\max}^{(u)} = \max_i C_i^{(u)}$
- idea: move jobs across clusters to optimize $C_{\max}$

Multi-objective optimization based on constraints on organizations' objectives

Parallel rigid jobs.

- an organization can not increase its local makespan $C_{\max}^{(u)}$ by cooperating with others
- schedule jobs locally (with makespan $C_{\max}^{(u)}(loc)$)
- optimization: $\min \max C_{\max}^{(u)}$ subject to $\forall u : C_{\max}^{(u)} \leq C_i^{(u)}(loc)$

Complexity

The problem is strongly NP-hard, even if each organization has only 2 jobs.

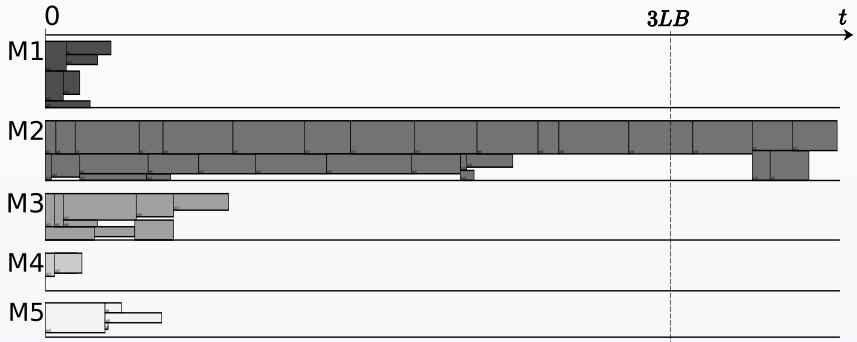
Lower bound of $\frac{3}{2}$ on the global makespan (easy instance).

Outline of the scheduling algorithm (MOCCA)

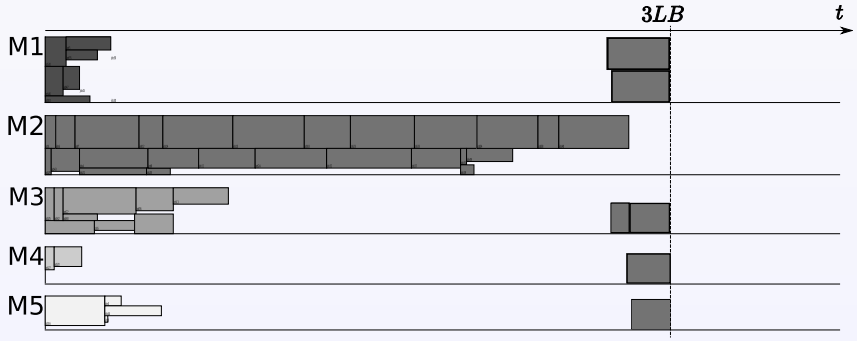
3-approximation of the global makespan where the local constraints are not violated

1. schedule jobs locally using highest-first (HF) ordering
2. unschedule jobs that complete after $3LB$ (LB is lower bound on the global makespan), sort them by HF
3. schedule large ($> m/2$) jobs backwards from $3LB$
4. schedule remaining jobs in the gaps of the schedule

Example run: first, we ensure the worst-case performance ...



(a) local scheduling



(b) MOCCA with gaps

Example run: . . . then, we collapse the schedule.

(b) MOCCA with gaps

(c) MOCCA, collapsed

Outline

Local versus Global

Strict constraints

MOSP's local and selfishness constraints are too strict in practice. They strongly limit the freedom of the scheduler to find a good global Cmax.

A clear trade-off

There is a correlation between the guarantees that we can provide individually for each organization and the global performance of the platform.

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MOSP's local and selfishness constraints are too strict in practice. They strongly limit the freedom of the scheduler to find a good global Cmax.

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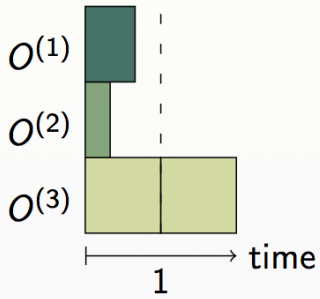
Question

How much can we improve the global Cmax of the entire platform if we allow some controlled degradation of the local performance?

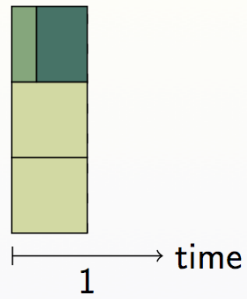
The α-Cooperative Multi-Organization Scheduling

Definition

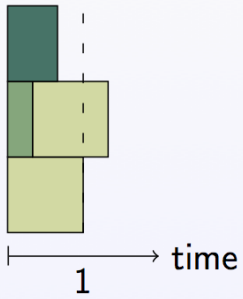
We denote as (α, β) a schedule that allows the local objectives to be degraded by a factor α in order to guarantee a β-approximation for the global Cmax.



(a) Initial instance

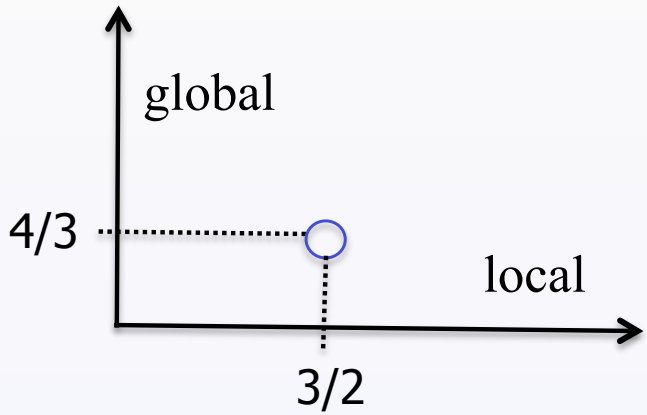


(b) $(\alpha = \frac{3}{2}; \beta = 1)$



(c) $(\alpha = 1; \beta = \frac{4}{3})$

Analysis of the **degree of cooperation** as a bi-objective problem.



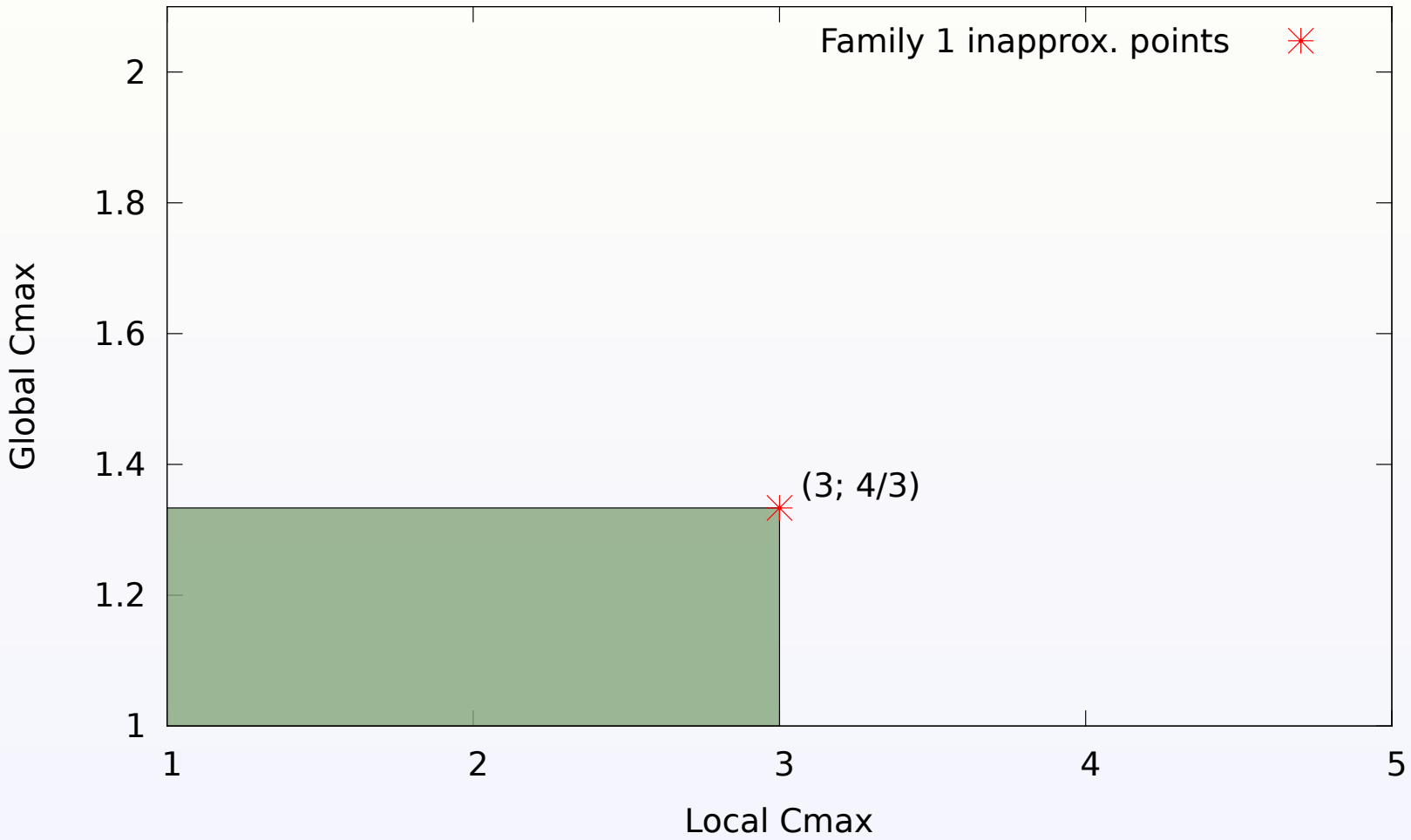


Figure : Inapproximation points given by Family 1 for $N = 4$

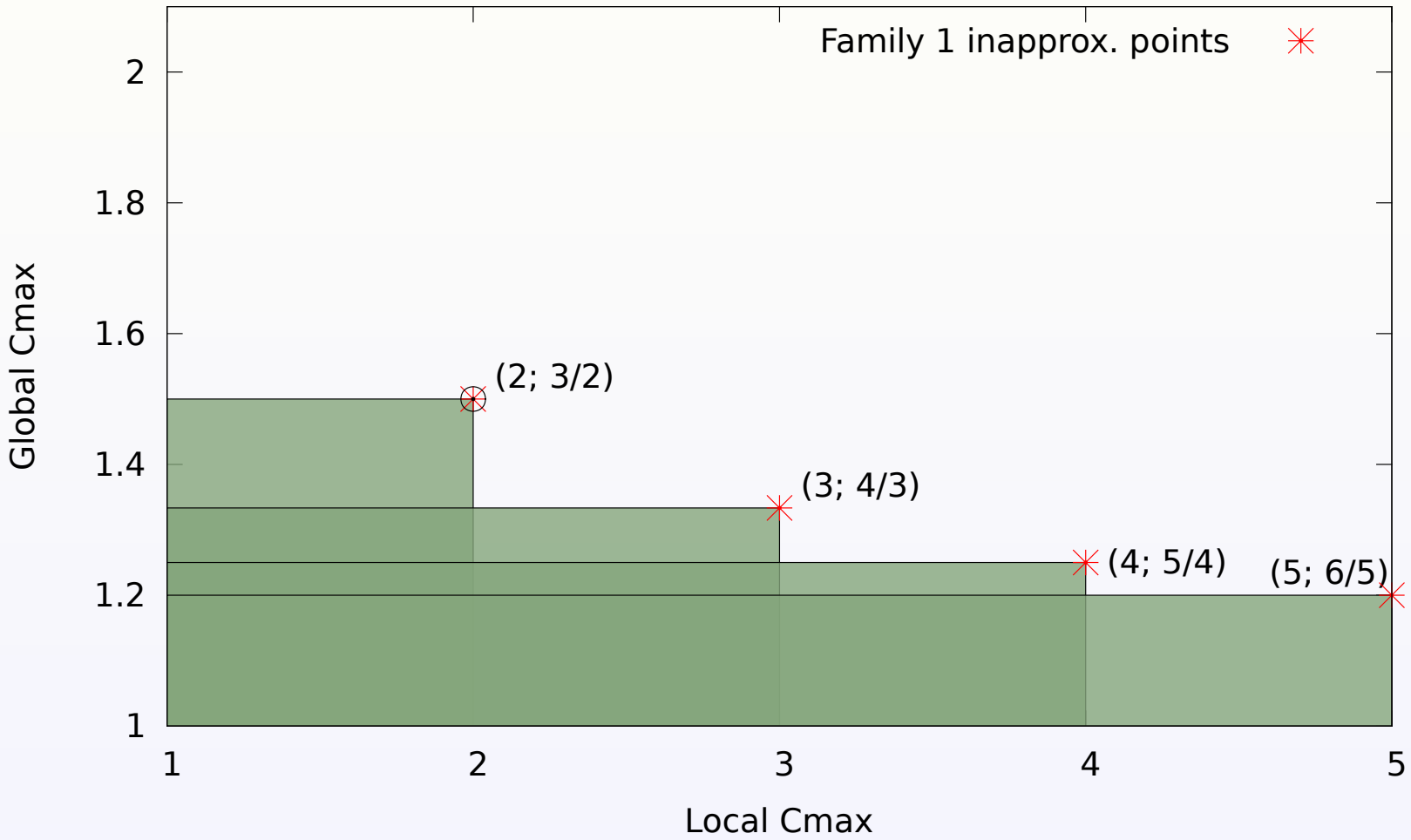
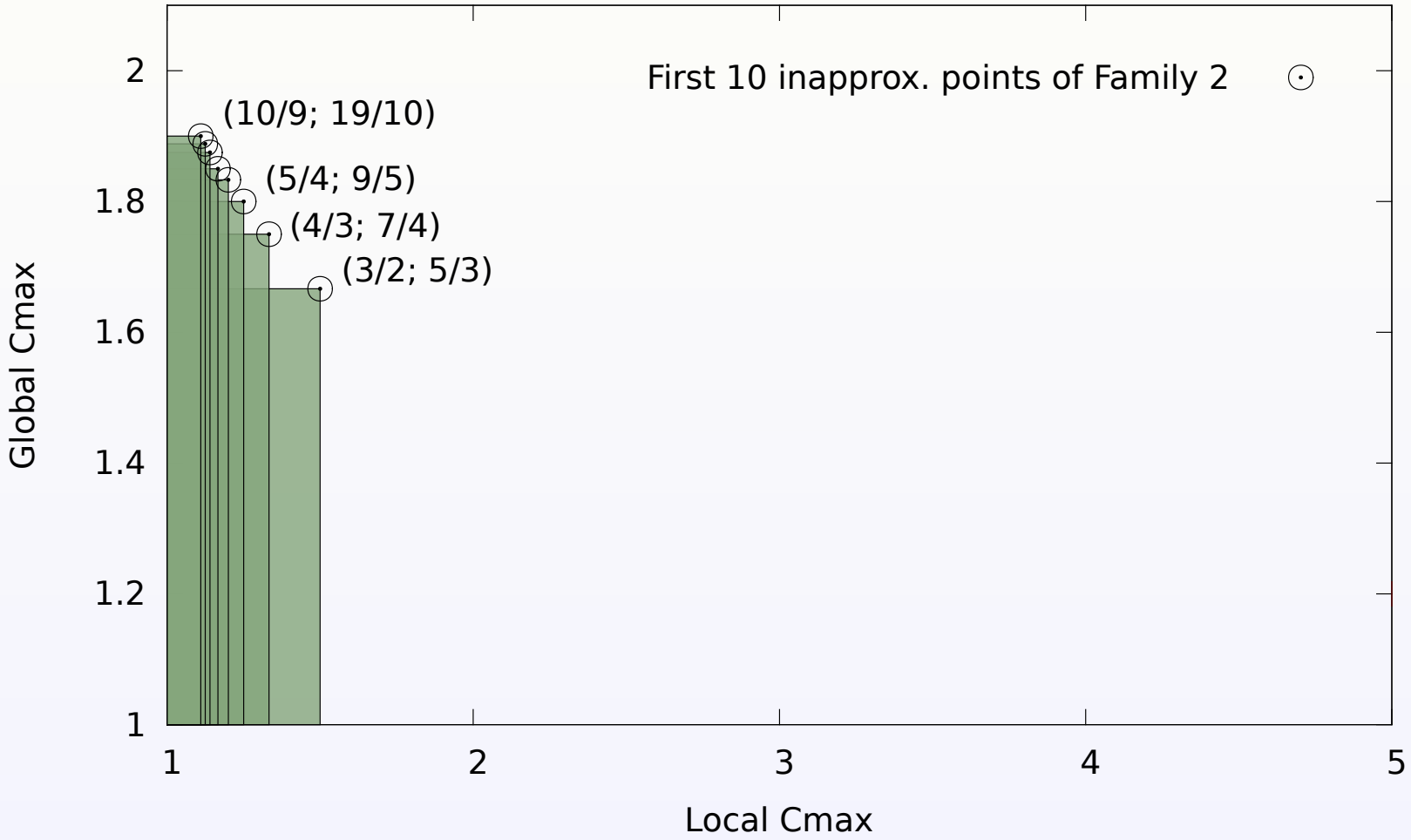
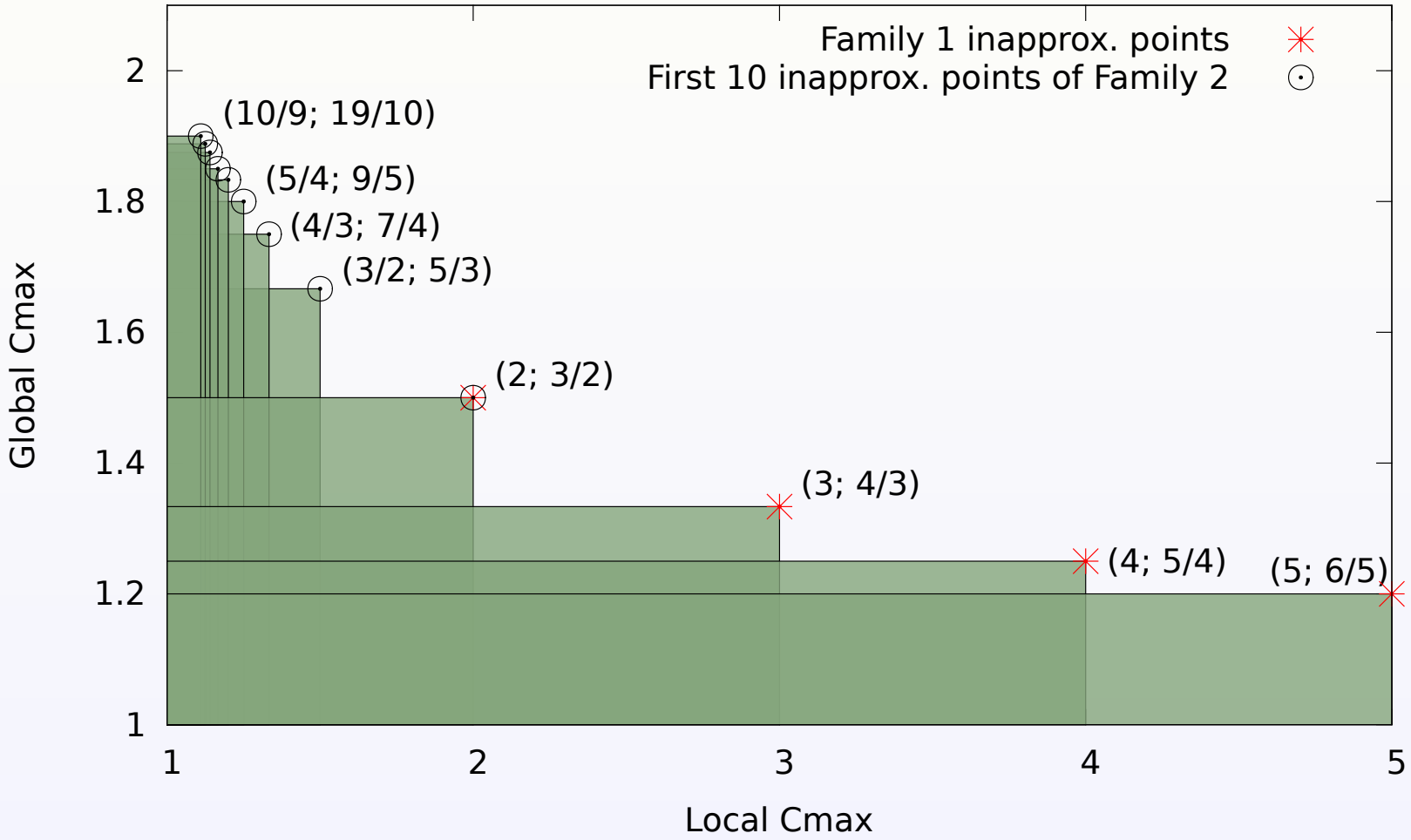
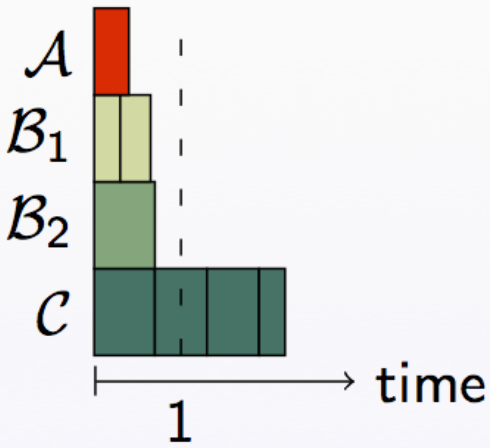


Figure : Inapproximation points given by Family 1 for $N = 3, 4, 5, 6$

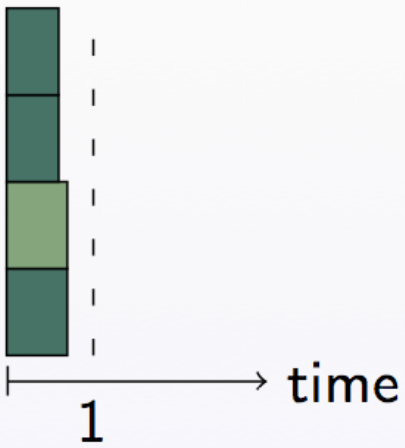

First 10 inapprox. points of Family 2
(10/9; 19/10)
(5/4; 9/5)
(4/3; 7/4)
(3/2; 5/3)
Global Cmax
Local Cmax
1
1.2
1.4
1.6
1.8
2
1
2
3
4
5


Family 1 inapprox. points
First 10 inapprox. points of Family 2
(10/9; 19/10)
(5/4; 9/5)
(4/3; 7/4)
(3/2; 5/3)
(2; 3/2)
(3; 4/3)
(4; 5/4)
(5; 6/5)
Global Cmax
Local Cmax
1
1.2
1.4
1.6
1.8
2
1
2
3
4
5

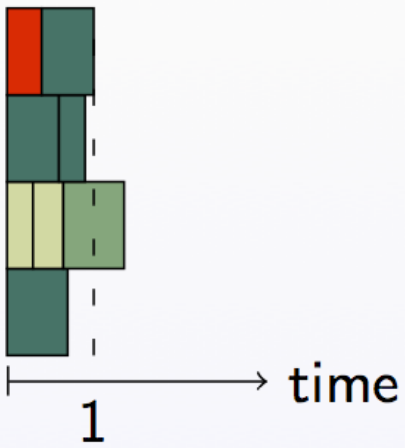
General principle of the algorithms



(a) Classification



(b) Place large jobs



(c) Pairing

We designed a two algorithms with approx $\left(2; \frac{3}{2}\right)$ and $\left(3; \frac{4}{3}\right)$.

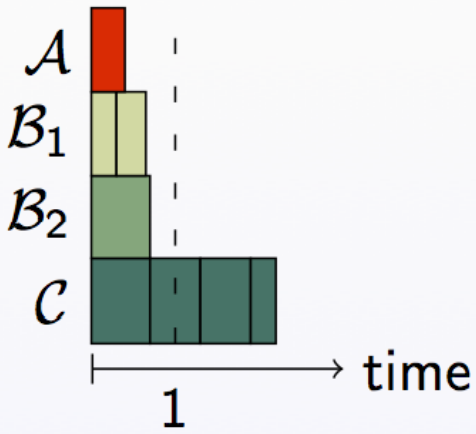


Figure : Classification

Algorithm 1:

- $\mathcal{A} = \{O^{(k)} \mid C_{\max}^{(k)\ local} \leq \frac{1}{2}\}$;
- $\mathcal{B}_1 = \{O^{(k)} \mid \frac{1}{2} < C_{\max}^{(k)\ local} \leq \frac{3}{4}$ and $\nexists\ J_i^{(k)}$ such that $p_i^{(k)} > \frac{1}{2}\}$;
- $\mathcal{B}_2 = \{O^{(k)} \mid \frac{1}{2} < C_{\max}^{(k)\ local} \leq \frac{3}{4}$ and $\exists!\ J_i^{(k)}$ such that $p_i^{(k)} > \frac{1}{2}\}$;
- $\mathcal{C} = \{O^{(k)} \mid C_{\max}^{(k)\ local} > \frac{3}{4}\}$.

We designed a two algorithms with approx $(2; \frac{3}{2})$ and $(3; \frac{4}{3})$.

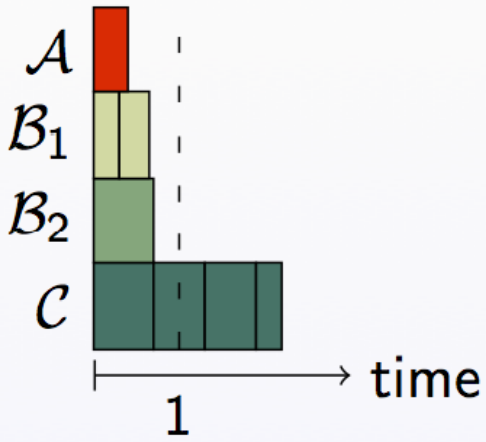
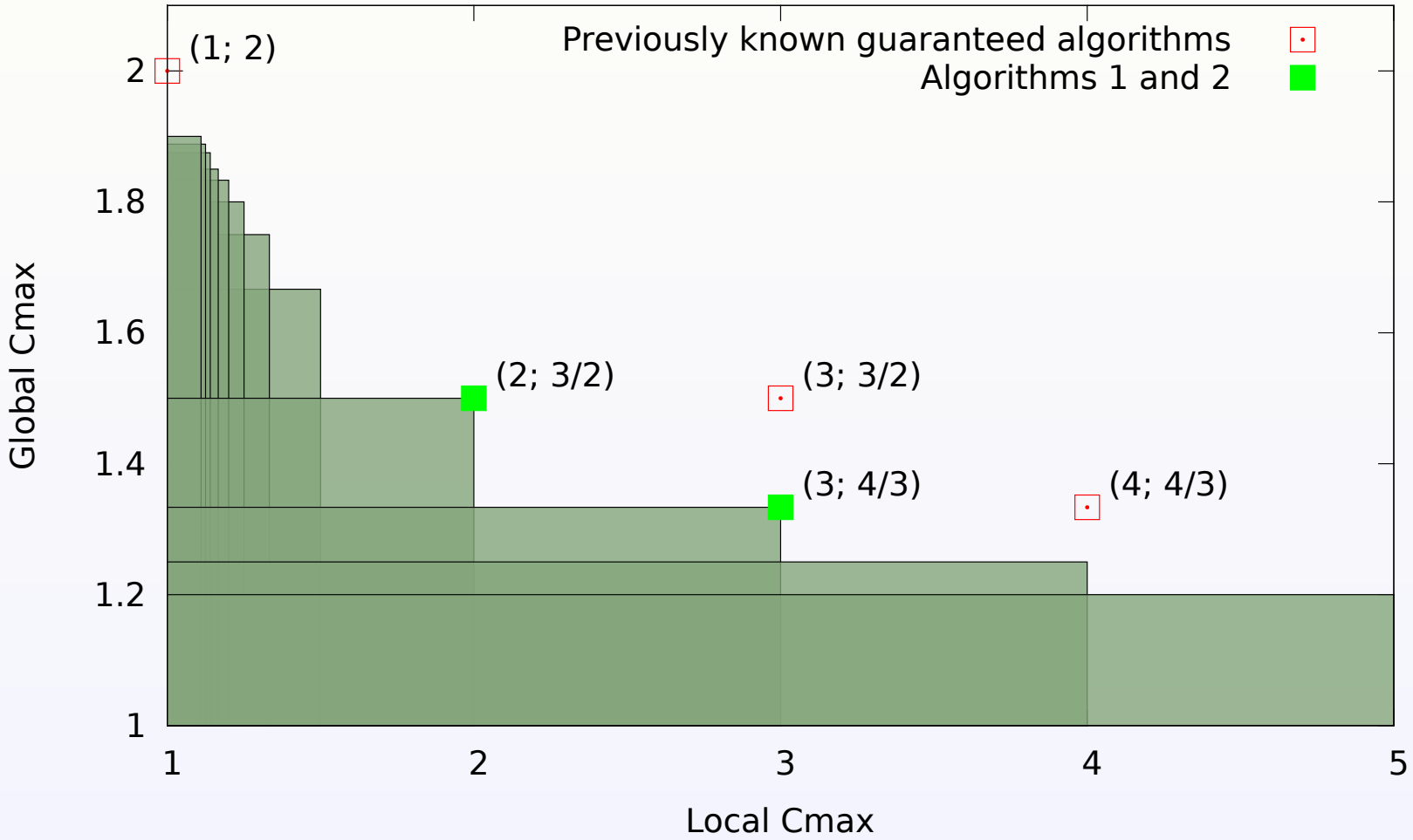


Figure : Classification

Algorithm 2:

- $\mathcal{A} = \{O^{(k)} \mid C_{\max}^{(k)\ local} \leq \frac{1}{3}\}$;
- $\mathcal{B}_1 = \{O^{(k)} \mid \frac{1}{3} < C_{\max}^{(k)\ local} \leq \frac{4}{9}$ and $\nexists\ J_i^{(k)}$ such that $p_i^{(k)} > \frac{1}{3}\}$;
- $\mathcal{B}_2 = \{O^{(k)} \mid \frac{1}{3} < C_{\max}^{(k)\ local} \leq \frac{4}{9}$ and $\exists!\ J_i^{(k)}$ such that $p_i^{(k)} > \frac{1}{3}\}$;
- $\mathcal{C} = \{O^{(k)} \mid C_{\max}^{(k)\ local} > \frac{4}{9}\}$.


Previously known guaranteed algorithms
Algorithms 1 and 2
(1; 2)
(2; 3/2)
(3; 3/2)
(3; 4/3)
(4; 4/3)
Global Cmax
Local Cmax
1
1.2
1.4
1.6
1.8
2
1
2
3
4
5

Outline

Concluding remarks

This talk illustrated a way of solving problems coming from the resource management in new cooperative parallel platforms.

Take home message

It was possible to study the problem by the degree of cooperation that could be imposed to the participants of the platform.

Current research directions

Put the user in the loop: in what extent it is possible to consider the individual objectives in such platforms?
The key notion here is the **fairness**.