

# A Practical 73/50 Approximation for Contiguous Monotone Moldable Job Scheduling

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Klaus Jansen   Felix Ohnesorge

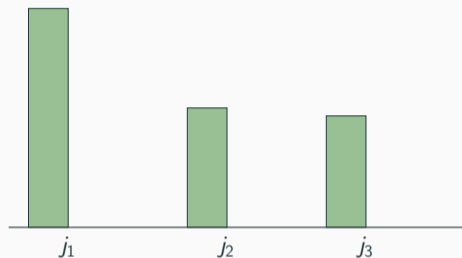
2026

Kiel University

# Moldable Scheduling

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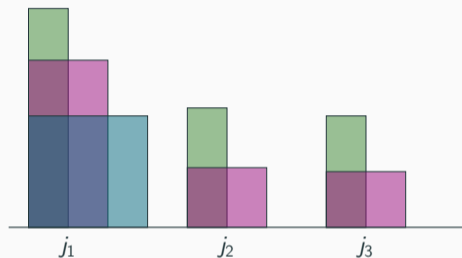
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- $n \in \mathbb{N}$  jobs.



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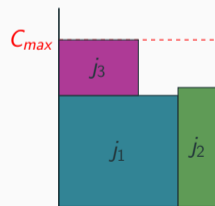
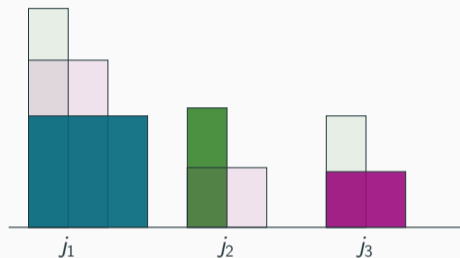
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  - Work function  $w_j : [m] \rightarrow \mathbb{Q}_{>0}$



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- Processing time  $p_j : [m] \rightarrow \mathbb{Q}_{>0}$ 
  - Work function  $w_j : [m] \rightarrow \mathbb{Q}_{>0}$
- Objective: **Minimize makespan**
  - $C_{max} = \max_{i \in [m]} C_i$

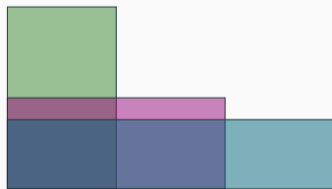


Schedule on  $m$  machines

## Monotony Assumption

The **processing-time function**  $p_j$  is non-increasing, for all  $j \in [n]$ .

- $k \leq k' \Rightarrow t_j(k) \geq t_j(k')$ .



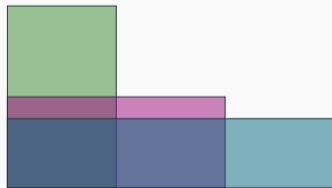
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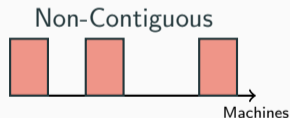
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- Each job  $j$  must be assigned to a set of **adjacent** machines  $\{i, i + 1, \dots, i + k - 1\}$ .



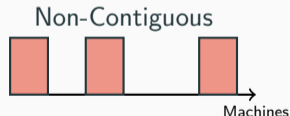
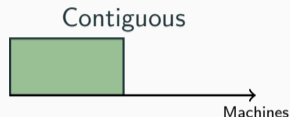
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## Motivation in HPC:

- Better memory locality.
- Reduced communication overhead between processing units.
- Simplified resource management.



## Related Work - Overview

Ratio, Condition	Complexity	Author (Year)
$1 + \varepsilon$	PTAS	Jansen, Thöle (2008)
$1 + \epsilon, m > 8 \frac{n}{\epsilon}$	$O(n \log(m)(\log(m) + \log(\frac{1}{\epsilon})))$	Jansen, Land (2018)
$\frac{5}{4} + \varepsilon$	$(nm)^{f(\frac{1}{\epsilon})}$	Jansen, Rau (2021)
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### Problem with the PTAS

For  $\varepsilon = 0.5$ , the PTAS has a running time of roughly  $nm^{2.4 \cdot 10^{17}}$ .

## Related Work - Overview of Algorithms Polynomial in $m, n$ , and $\frac{1}{\epsilon}$

Ratio	Complexity	Author (Year)
$3/2 + \epsilon$	$O(nm \log(1/\epsilon))$	Mounié, Rapine, Trystram (2007)
$3/2 + \epsilon$	$O(\frac{n}{\epsilon^2} \log m (\frac{\log m}{\epsilon} + \log^3(\epsilon m)))$	Jansen, Land (2018)
$3/2 + \epsilon$	$O(n \log^2(\frac{1+\log(\epsilon m)}{\epsilon}) + \dots)$	Grage, Jansen, O. (2023)
$3/2$	$O(nm \log(nm))$	Wu, Zhang, Chen (2023)
$1.4593 + \epsilon$	$O(nm \log(1/\epsilon))$	<b>This Work</b>

# Dual-Approximation Framework - Hochbaum & Shmoys (1985)

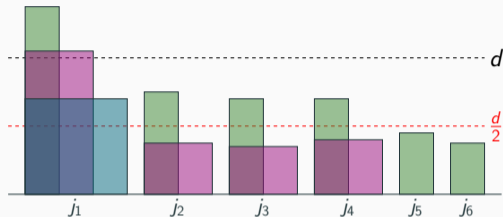
1. Find bounds on optimum:  $\ell \leq d^* \leq u$ .
2. Binary search on makespan guesses  $d$ :
  - a) Either decide no schedule with makespan  $\leq d$  exists,
  - b) or build schedule with makespan  $\leq \lambda d$ .

$\Rightarrow$  Yields a  $(\lambda + \varepsilon)$ -approximation with  $O(\log \frac{1}{\varepsilon})$  search steps.



### Definition: Small Jobs

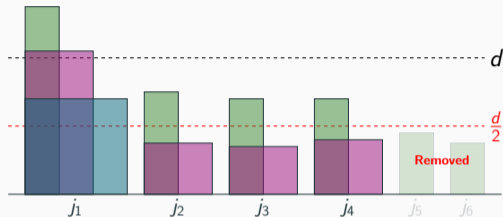
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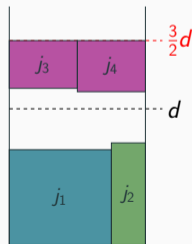
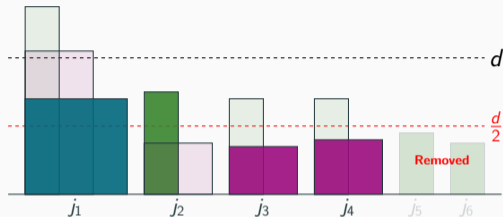


## Previous Work - Mounié et al. (Outline)

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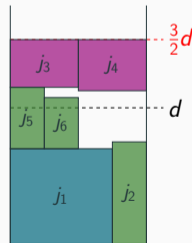
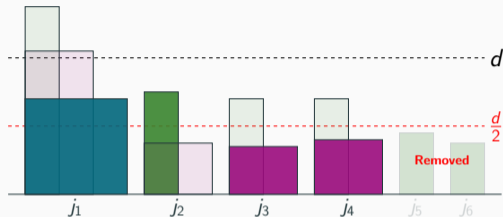


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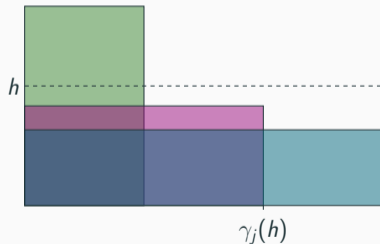


# Canonical Number of Machines

## Definition

$\gamma_j : \mathbb{Q}_{>0} \rightarrow [m]$ , such that:

- $\gamma_j(h)$  is the minimal number of machines to execute job  $j$  in time  $h$ .



### Theorem (Mounié et al.)

Given a partition of tasks  $S_1 \sqcup S_2 = J_B$  s.t.

1.  $\sum_{j \in S_1} w_j(\gamma_j(d)) + \sum_{j \in S_2} w_j(\gamma_j(d/2)) \leq md$
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one can compute a schedule with length **at most**  $\frac{3}{2}d$  in time  $O(mn)$ .

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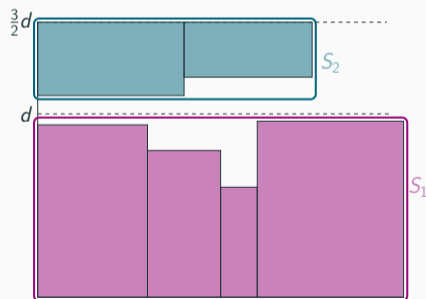
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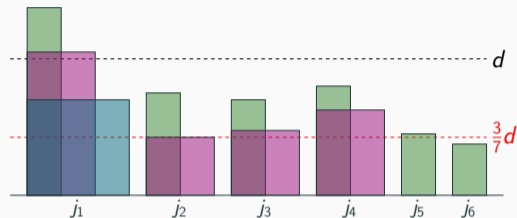
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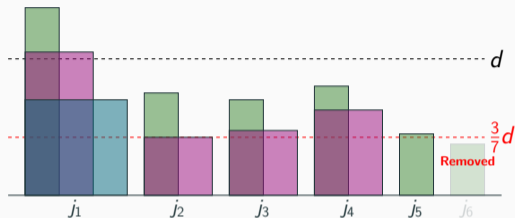


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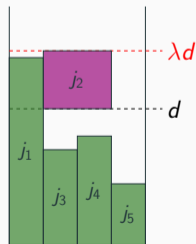
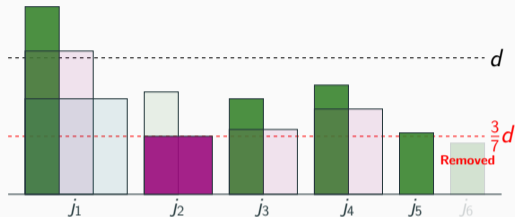


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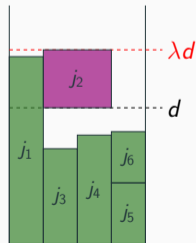
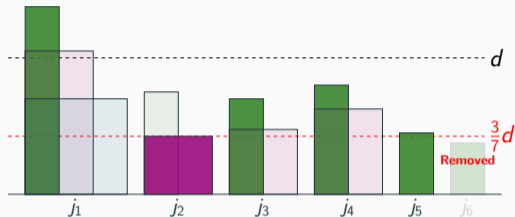


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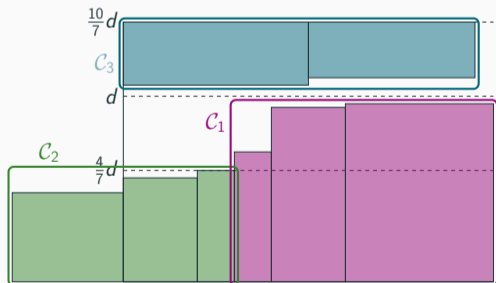
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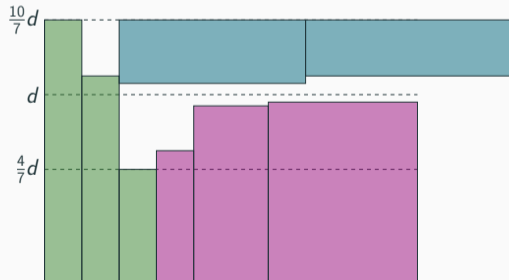
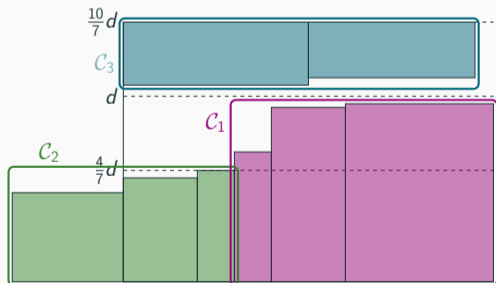
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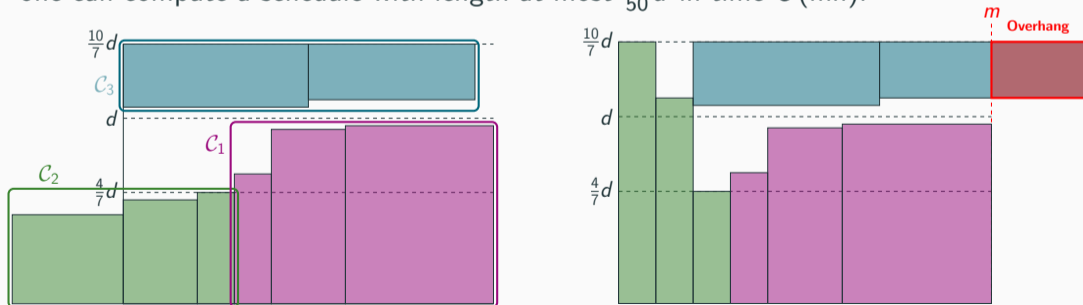
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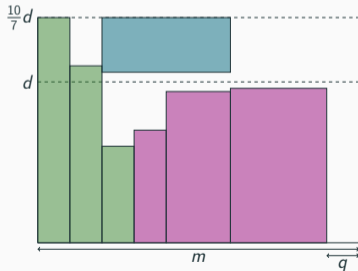
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# Repairing the Schedule

## Case 1: Schedule is feasible

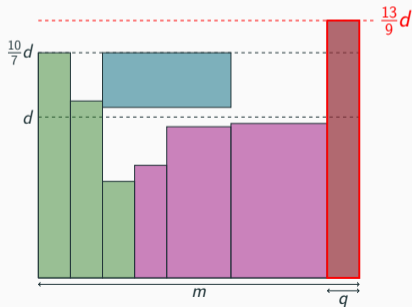
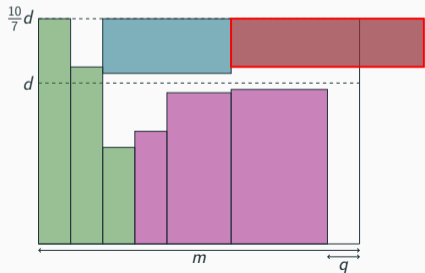
Guaranteed ratio of  $\frac{10}{7}$ . Everything fits within the machine bounds.



# Repairing the Schedule

**Case 2: Simple Case** ( $q \leq \frac{m}{6}$ )

Guaranteed ratio of  $\frac{13}{9}$ .



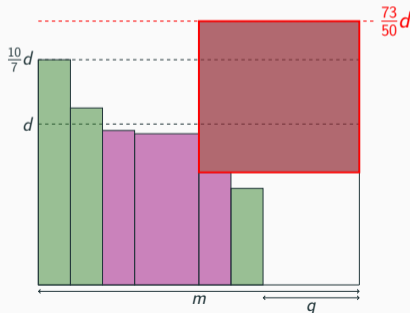
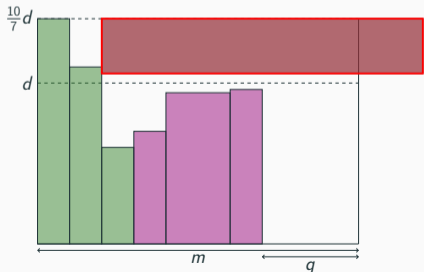
# Repairing the Schedule

## Case 3: Critical Case ( $q > \frac{m}{6}$ )

Guaranteed ratio of  $\approx 1.4593$ .

### Key Observation

If  $q > m/6$ , then  $\mathcal{C}_3$  contains **exactly one job**.



# Results

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## Our Results for Contiguous Monotone Moldable Scheduling

Our algorithm produces a **contiguous schedule** with an approximation ratio of  $\approx 1.4593 + \epsilon$ .

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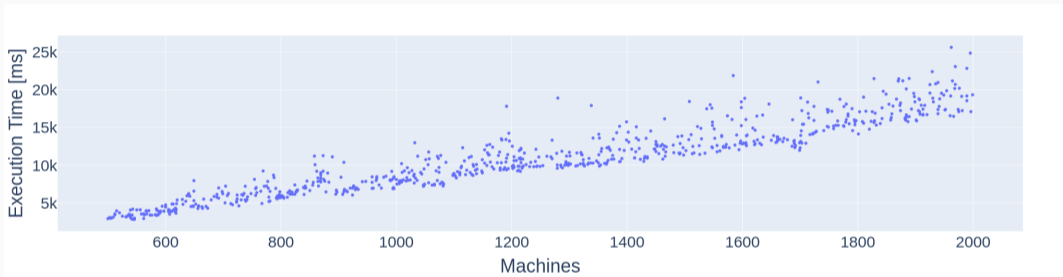
Our algorithm produces a **contiguous schedule** with an approximation ratio of  $\approx 1.4593 + \varepsilon$ .

## The Contiguity Gap

- We compare our contiguous makespan to the **non-contiguous lower bound**.
- Result: The makespan gap between optimal contiguous and non-contiguous schedules is **bounded by our ratio**.

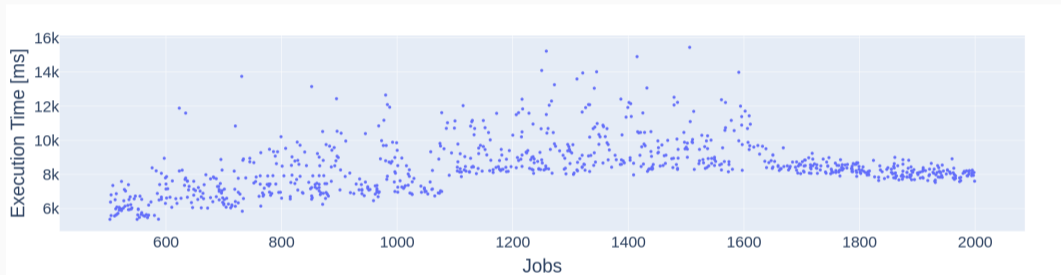
- Implementation in Java (available on GitHub)
- Tested on a single core of an Intel i5-8400T CPU with 2GB RAM
- Two sets of tests:
  - Varying number of machines ( $m$ ) with fixed number of jobs ( $n = 1000$ )
  - Varying number of jobs ( $n$ ) with fixed number of machines ( $m = 1000$ )

## Practical Results - Runtime



**Figure 1:** Execution Time of the Implementation for Varying Number of Machines.

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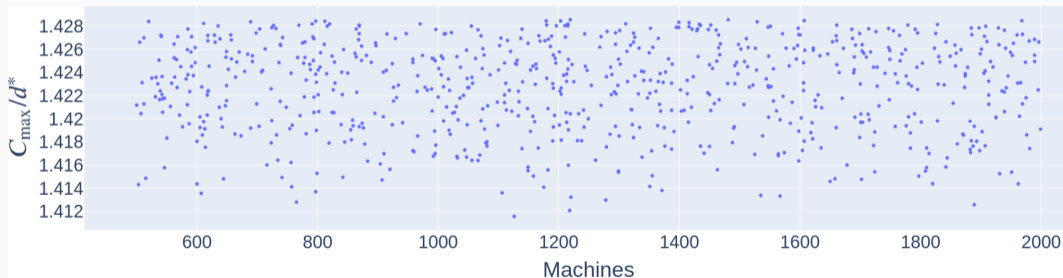


**Figure 1:** Execution Time of the Implementation for Varying Number of Jobs.

## Practical Results - Approximation Ratio

$d^*$  is the last makespan guess of the dual approximation framework. Thus:

$$d^* \leq (1 + \varepsilon)\text{OPT} = 1.05 \cdot \text{OPT}.$$

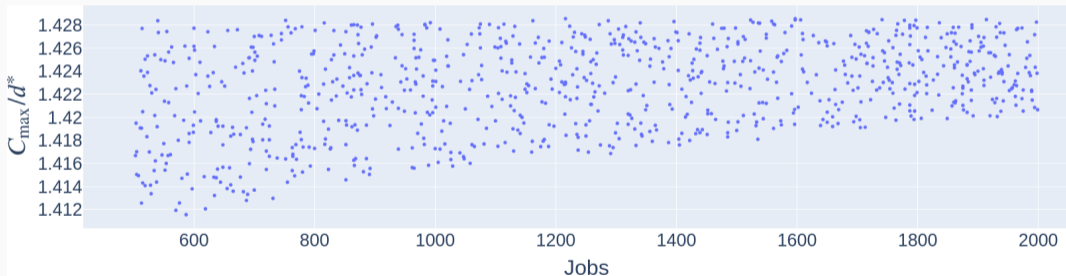


**Figure 2:** Approximation Ratio of the Implementation for Varying Number of Machines.

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$d^*$  is the last makespan guess of the dual approximation framework. Thus:

$$d^* \leq (1 + \varepsilon)\text{OPT} = 1.05 \cdot \text{OPT}.$$



**Figure 2:** Achieved Approximation Ratio of the Implementation for Varying Number of Jobs.

## Future Work

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Thank you for your attention!

## Omitted Slides

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# The Geometric Analysis

If the algorithm fails, the load  $L_i$  on each machine  $i$  is greater than:

$$g(i) = \lambda d - \frac{dm - \frac{\lambda}{2}d(m - q)}{m - i}$$

## Bounding the Work Area

We can bound the total work on Shelf 1 ( $W_1$ ) using an integral over this curve:

$$W_1 > \int_0^{m-q} \max \left\{ g(i), \frac{\lambda}{2}d \right\} di$$

Adding the work of  $W_2$ , we find the minimum of this function occurs at  $q = \frac{\lambda-1}{\lambda}m$ .

## The Lambert W Function

Solving the integral inequality

$W_1 + W_2 > md$  yields:

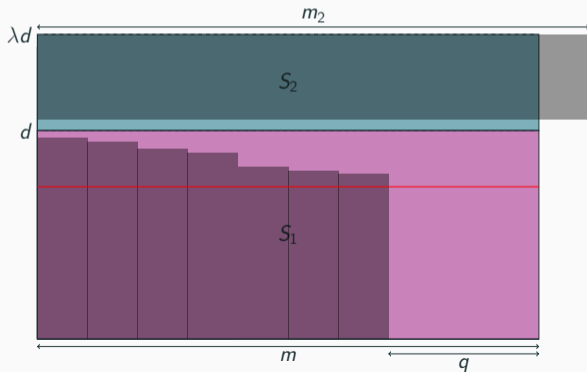
$$-3\lambda e^{-3\lambda} > -3e^{-4}$$

Which is solved using the  $W_{-1}$  branch of the Lambert W function:

$$\lambda > -\frac{1}{3}W_{-1}(-3e^{-4}) \approx 1.4593$$

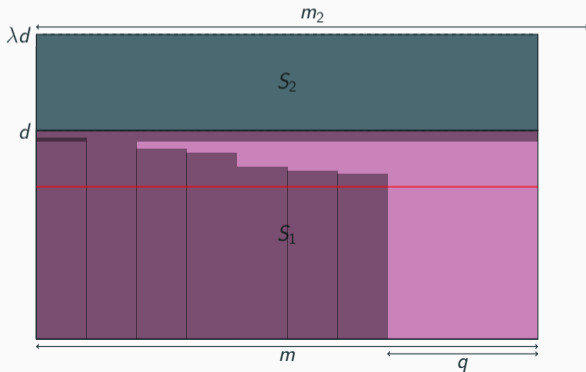
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- Try every possible allotment of the job in  $S_2$ .



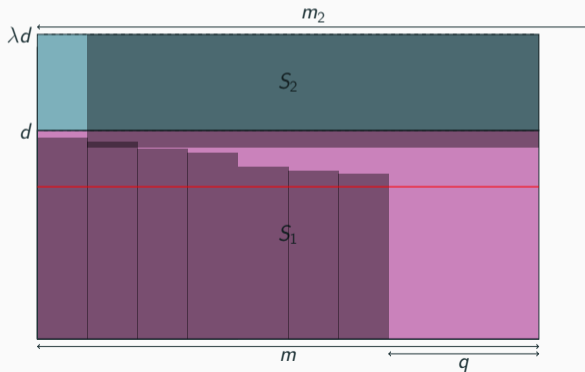
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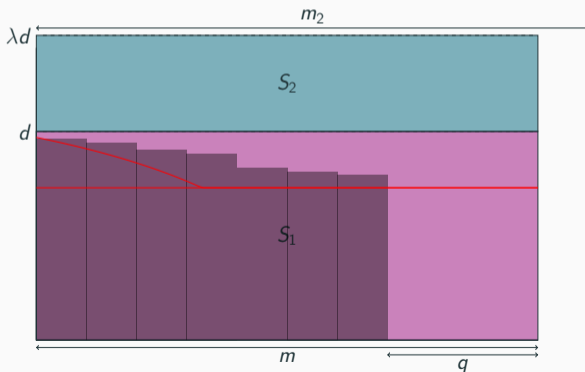
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- Try every possible allotment of the job in  $S_2$ .
- If the job does not fit, the load of each machine  $i$  in  $S_1$  is greater than  $\max(\frac{\lambda d}{2}, g(i))$ , with  $g(i) = \lambda d - \frac{dm - \frac{\lambda}{2}d(m-q)}{m-i}$



## Related Work

Ratio	Complexity	Author (Year)
$\frac{3}{2} + \epsilon$	$O(\log(1/\epsilon)nm)$	Mounié, Rapine, Trystram (2007)
$1 + \epsilon$ $\frac{3}{2} + \epsilon$	$O(n \log(m)(\log(m) + \log(\frac{1}{\epsilon})))$ $O(\frac{n}{\epsilon^2} \log m(\frac{\log m}{\epsilon} + \log^3(\epsilon m)))$	Jansen, Land (2018)
$1 + \epsilon$ $\frac{3}{2} + \epsilon$	$O(n \log^2(\frac{1}{\epsilon} + \frac{\log(\epsilon m)}{\epsilon}))$ $O(n \log^2(\frac{1 + \log(\epsilon m)}{\epsilon}) + \frac{n}{\epsilon} \log(\frac{1}{\epsilon}) \log(\epsilon m))$	Grage, Jansen, O. (2023)
$\frac{3}{2}$	$O(nm \log(nm))$	Wu, Zhang, Chen (2023)
$\frac{73}{50} + \epsilon$	$O(\log(1/\epsilon)nm)$	This Work