Algorithms for Dynamic Right-Sizing in Data Centers

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Dynamic Right-Sizing

Dynamically adjust the number of active servers and efficiently distribute the varying workloads



Model and Problem Formulation

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Notation:

• $x_1, \ldots, x_T \in \{0, \ldots, m\}$... Numbers of active servers

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$$\sum_{t=1}^{T} \left(\underbrace{c_{op}(x_t, \lambda_t) + \beta \max\{0, x_t - x_{t-1}\}}_{c(x_{t-1}, x_t, \lambda_t)} \right)$$

Optimal Offline Algorithm

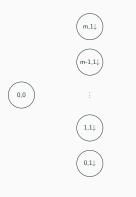
Fundamental idea: reduce problem to shortest path problem

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0,0

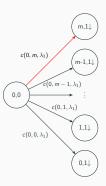
Time complexity: $\Theta(Tm)$

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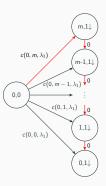
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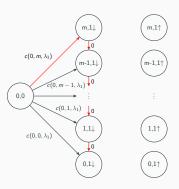
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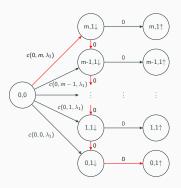
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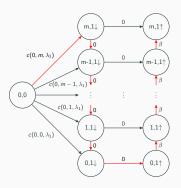
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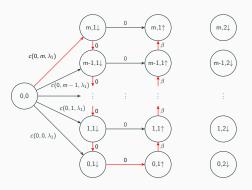
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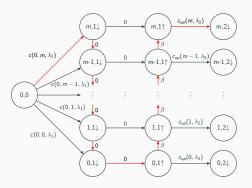
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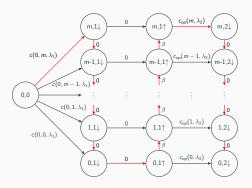
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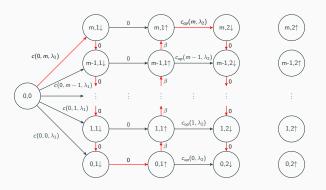
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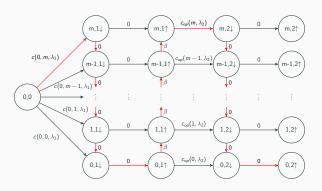
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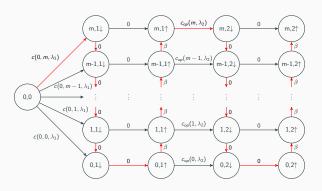
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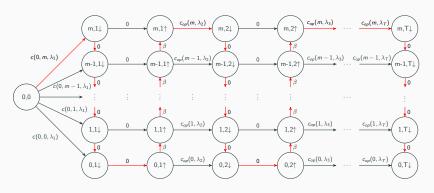
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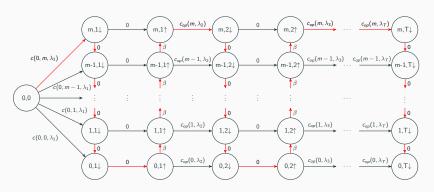


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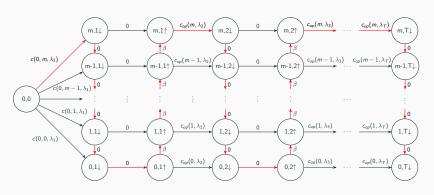


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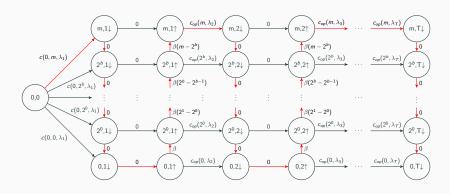
Offline Approximation Algorithm

2-Optimal Linear-Time Algorithm

Use logarithmic steps to reduce number of nodes

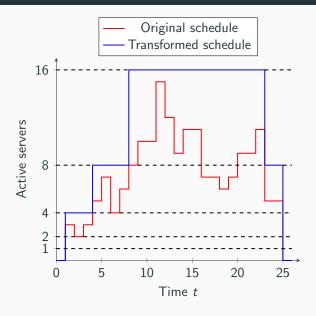
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where
$$b := \lfloor \log_2(m) \rfloor$$

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Approximation for arbitrary precision $\varepsilon>0$ with time complexity $\Theta \left(T \log_{1+\varepsilon}(m) \right)$

Summary and Prospects

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We reduced the scheduling problem to the shortest path problem of acyclic graphs.

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(1+arepsilon)-Optimal Offline Algorithm with linear runtime $\Thetaig(T\log_{1+arepsilon}(m)ig)$

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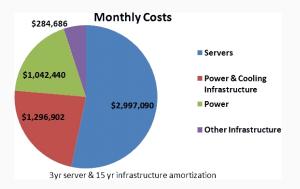
Open question: Is there a polynomial optimal algorithm or is it an NP-hard problem?

Thanks for your attention!

Any questions?

Data Centers' Costs

Fast-growing demand for data collection, processing, and storage

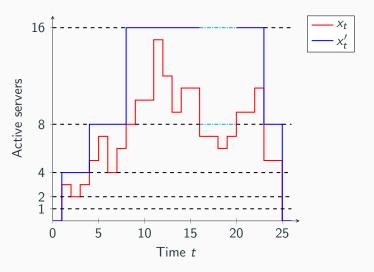


Proof Idea

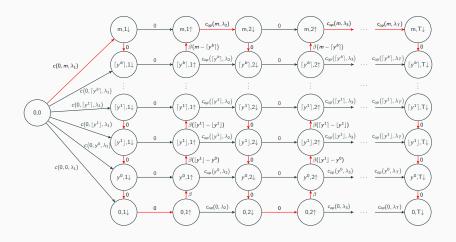
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$(1+\varepsilon)$ -Optimal Offline Algorithm



where $y := 1 + \varepsilon, b := \lfloor \log_y(m) \rfloor$

Image Sources I

- Data center: datacentervoice.com/wp-content/ uploads/2015/12/data-center.jpg
- Data center costs: perspectives.mvdirona.com/2008/11/ cost-of-power-in-large-scale-data-centers/