

Scheduling Resources for Executing a Partial Set of Jobs

Venkat Chakravarthy, Arindam Pal, Sambuddha Roy¹, Yogish Sabharwal

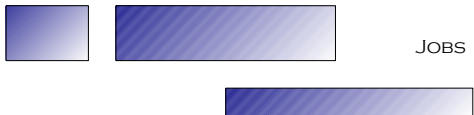
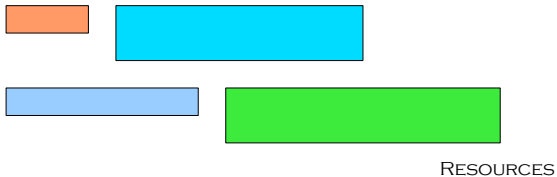
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A Typical Scheduling Scenario

- We are given a collection of jobs. Each job is an interval, with attributes: *starting time*, *ending time* and *capacity requirement*.
- We are also given a collection of resources; resources are also intervals. A resource interval has attributes *starting time*, *ending time*, *capacity* and also an associated *cost*.

An example scenario



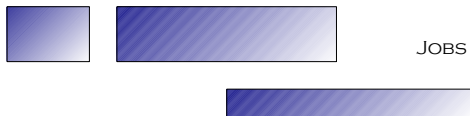
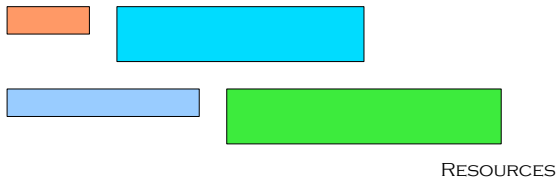
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- When does a resource *cover* a job? If it
 - (a) spans the length of the job, and
 - (b) the capacity of the resource is sufficient to fulfill the capacity requirement of the job.
- Generalize this notion to *collection of resources*, and *collection of jobs*. A collection of resources *covers* a collection of jobs, if at any point of time, the total capacity of resources available is sufficient to fulfill the capacity requirements of the jobs active at that time point.
- **Overall Objective:** To fulfill (i.e. complete) the jobs using a *minimum cost* collection of resources.
- Call this the `ResAll` problem.

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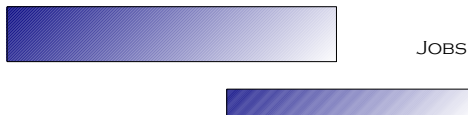
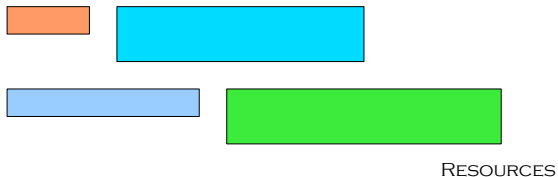
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Two Variants of ResAll

- Resources may be picked at most **once** (the $\{0, 1\}$ version) or **multiple times** (the multiplicity version).
- Both variants have a 4-factor approximation [BarNoy et al.01].
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- Often it is the case that not all the jobs in the collection need to be fulfilled, but there are SLA requirements such as: “satisfy 90% of the jobs”.
- Scenarios where such problems arise naturally: call center optimization, sensor networks, cloud computing, energy management ...

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Problem Definition

- Formally, we are given a collection \mathcal{R} of $m \in \mathbb{N}$ *resource intervals*. Each resource type has a **cost** per unit of the resource.
- Thus, a resource interval i is equipped with a “height” h_i (the *proficiency or capacity* of the resource) cost c_i , starting time s_i and ending time e_i .
- We are also given a collection \mathcal{J} of $n \in \mathbb{N}$ *job intervals*. Each job interval j has a starting time s_j , ending time e_j and a height h_j (i.e. capacity requirement).

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The SLA requirement

- We are also given a number k ($1 \leq k \leq n$), that corresponds to the SLA requirement: the number of *jobs* that need to be fulfilled.
- The **objective** is to select a minimum cost collection of resource intervals from \mathcal{R} so that at least k of the jobs in \mathcal{J} are satisfied.
- Call this problem the `PartialResAll` problem (it is NP-hard – Minimum Knapsack Cover is a special case).
- This is a *partial covering* problem, where only a certain fraction of the total collection of jobs need to be covered.

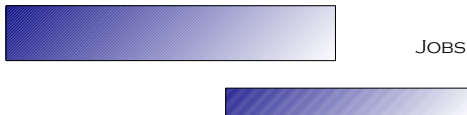
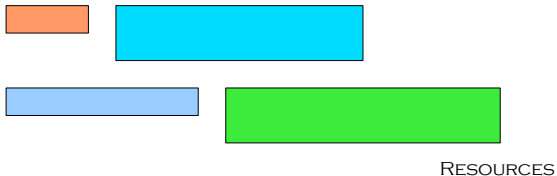
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RESOURCES TO COVER JOBS; $K = 1$

Ambient space of our problem

- Instances of covering problems abound: Set Cover, Vertex Cover, Minimum Spanning Tree, Steiner Network etc.
- Any such covering problem has a **partial covering** variant.
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History of Partial Covering problems

- 2-factor approximations for the Partial Vertex Cover problem [Bar-Yehuda99, Gandhi-Khuller-Srinivasan01, Mestre07].
- The k -Median problem has constant factor approximations; methods are based on Lagrangian Relaxations [cf. JainVazirani99]
- 2-factor approximations for the k -MST problem [Garg05]
- etc. . .

Holy Grail

- The most general problem in this direction is to prove a constant factor approximation for the $\{0, 1\}$ version of the `PartialResAll` problem.



Main Result

- Here we consider the following *restriction* of the `PartialResAll` problem:
 - The **multiplicity** version: resources are allowed to be picked multiple times.
 - Jobs have **unit** height.
- Call this problem the restricted `PartialResAll` problem.

Theorem

There is a polynomial time $O(\log \ell_{\max}/\ell_{\min})$ -factor approximation for the restricted `PartialResAll` problem.

Here, ℓ_{\max} and ℓ_{\min} stands for the longest and shortest lengths of the **jobs**. Note that this can be easily seen to be bounded by n , the *number* of jobs.

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- Recall that for the `ResAll` problem ($\{0, 1\}$ or multiplicity versions), a 4-factor approximation was known [BarNoy et al.01].
- Only special cases of the `PartialResAll` problem have been considered in the literature. The case where resources can be picked multiple times, and where jobs have arbitrary height, but **unit length** was considered in [Chakravarthy et al.11]. They show that in this special case, the `PartialResAll` problem has a 16-factor approximation.
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- From now on, all jobs will have **unit** height, and resources can be picked multiple times.
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The overall theme

- We would like to simplify the structure of jobs.
- We can do a decomposition according to job lengths to reduce the general problem to the following special case, where the jobs form a so-called **mountain range**.
- This happens at a loss of $O(\log \ell_{\max}/\ell_{\min})$ -factor.
- This is similar to the work of [Bansal et al.09] – they gave a logarithmic approximation for the UFP problem on a line.
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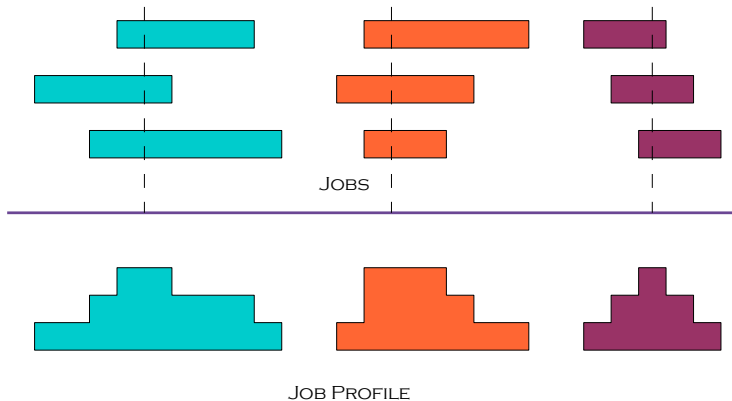
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Example Mountain Range



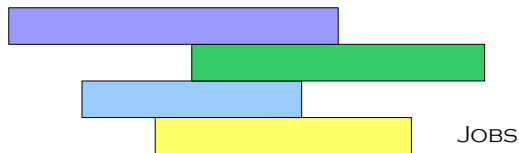
Mountain Ranges

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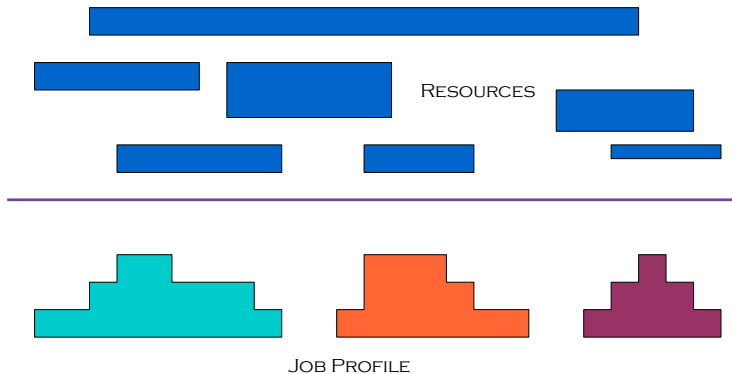


A SINGLE MOUNTAIN

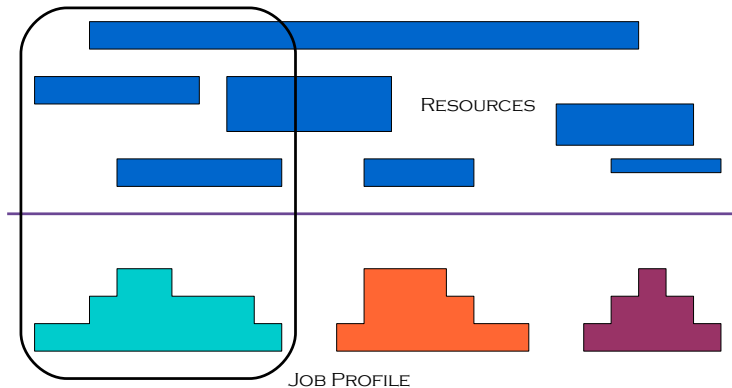
A Natural Algorithm for a Single Mountain

- Recall that all jobs have the same height. A natural idea is to *drop* jobs that extend farthest to the right (or to the left) while still observing the partiality constraint.
- This actually works: this yields a 8-factor approximation for the case of a single mountain.

Back to a mountain range



Back to a mountain range



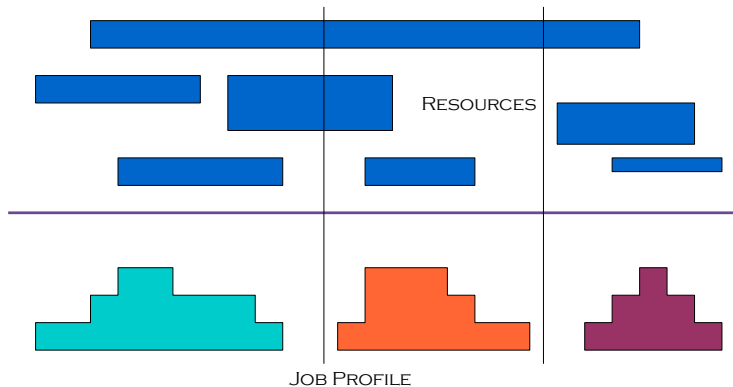
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- Why does the problem concerning a mountain range not decompose into multiple single mountains?
- Because resources can span multiple single mountains of a mountain range.

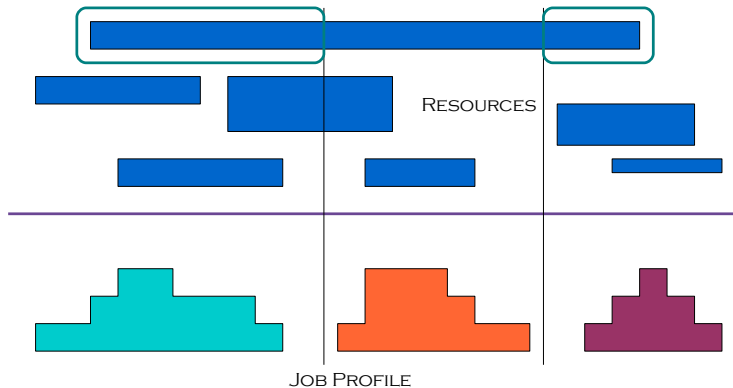
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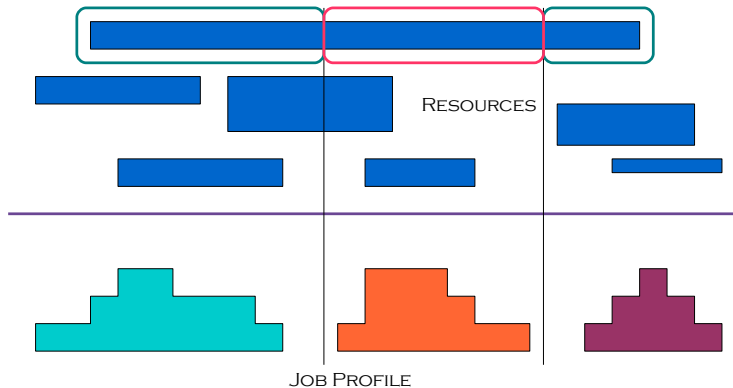
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Resource Decomposition

- We decompose resources so that a resource fully spans a collection of (consecutive) single mountains (a **long** resource), or that a resource is contained in the span of only a single mountain (a **short** resource).
- This happens at a factor 3 loss.
- We can now “shrink” the mountains in a mountain range to **timeslots**, and thus we can modify our problem so that all the jobs are now **one timeslot long**.

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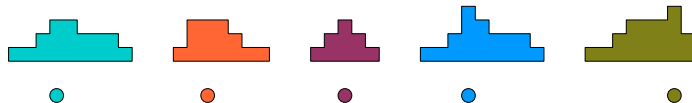
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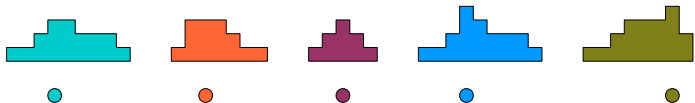
JOB PROFILE

Resource Decomposition



MOUNTAINS SHRUNK TO TIMESLOTS WITH DEMAND = PEAK OF MOUNTAIN

Resource Decomposition

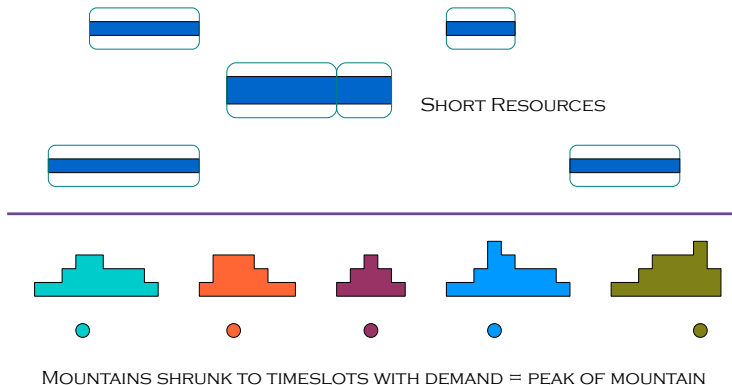


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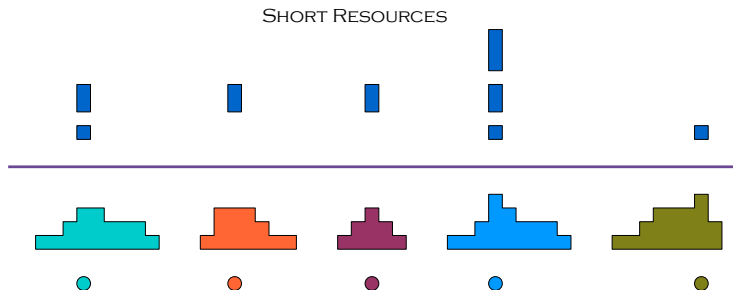
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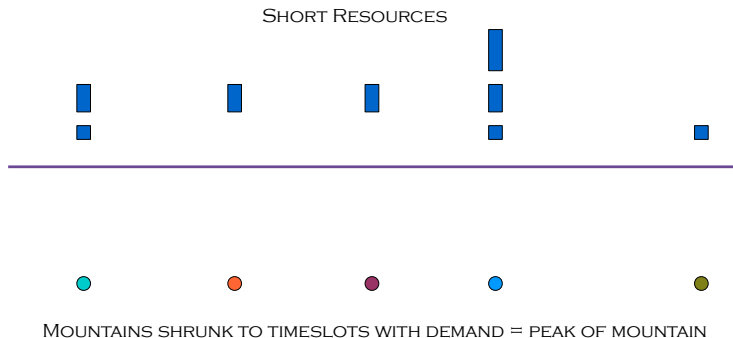
- The short resources along with the corresponding mountain form a “single mountain” `PartialResAll` problem.
- Solve this `PartialResAll` problem for various values of the partiality parameter k .
- For each (approximate) solution, place a resource of unit length on the corresponding timeslot of cost equal to that of the solution, and capacity equal to k .

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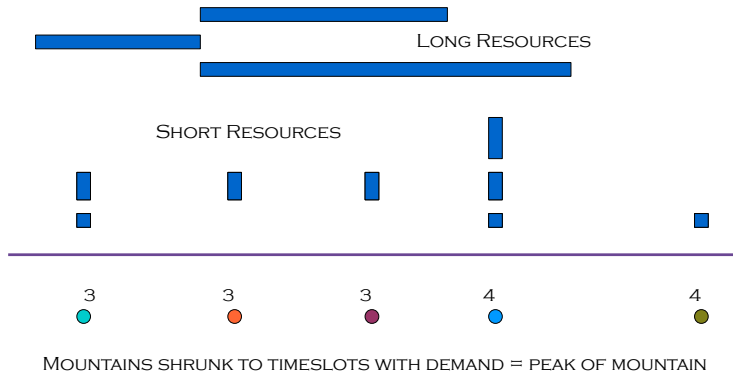


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The long and short of it...



- Short resources comprise of a collection of (short) resources, so can be picked only once.
- Long resources are (parts) of original resources, so can be picked multiple times.
- What has happened to the partiality? We now need to pick up k of the cumulative demands d_t .

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Ruminations

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- However, here the only resources restricted to be picked up at most once are the *short* resources.
- If only the long resources were present, we get a 16-factor approximation algorithm, via [Chakravarthy et al.11]. Why?
- If only the short resources are present, a simple DP gives the optimal solution.
- When both types of resources exist, a (slightly involved) amalgam of the DP solutions gives a 16-factor approximation for this “short resource, long resource” problem.

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Main Result

- This completes a proof sketch of the $\log(\ell_{\max}/\ell_{\min})$ -factor approximation for the restricted case of `PartialResAll`.

Auxiliary Result

- One can also define the “Prize Collecting” version of ResAll . We prove a 4-factor approximation for the Prize Collecting version.
- However, this approximation algorithm does not have the so-called LMP (Lagrangian Multiplier Preserving) property (as in the framework of [JainVazirani99]).
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- To prove a constant factor approximation for the $\{0, 1\}$ version of the `PartialResAll` problem.
- As a first step, prove this for the case where jobs are timeslots with demands (i.e. jobs have unit lengths).
- Remove the restriction of *unit heights* in the result discussed.
- Prove better hardness results. Strong NP-hardness?



THANK YOU.