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Find a configuration that minimizes or maximizes an objective function.

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- Greedy algorithms that actually obtain a global optimum often do not exist.
- Greedy algorithms are usually simple, but the proof of correctness may not be so simple.
- ▶ We will give several examples of greedy algorithms.

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- In the zero-one version of the problem, we either include all of each object or none of it.
- ► For now, we will consider just the fractional version.

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and

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Implementation detail:

Sort items in decreasing order of value density:

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- Alternatively, implement using a max-heap. (Key of each object is its value density.)
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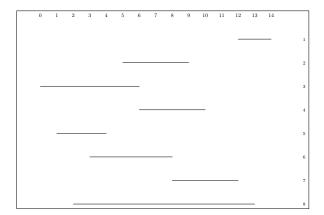
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- ▶ Find the minimum number of required machines.

Task scheduling problem example

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Example: 8 tasks: $\{(12, 14), (5, 9), (0, 6), (6, 10), (1, 4), (3, 8), (8, 12), (2, 13)\}$

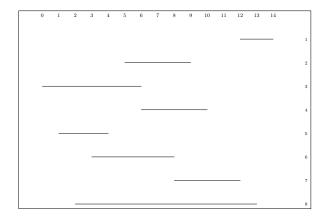


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0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	
-						_									3
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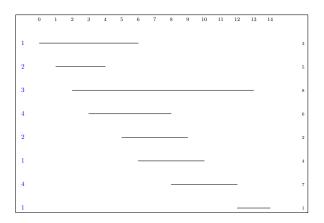
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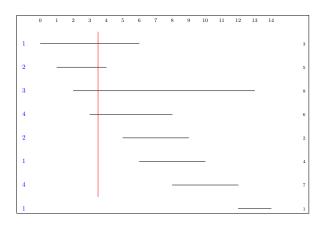
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([GT] problem A-10.2)

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Example: 8 tasks (same tasks as previous problem): $\{(12, 14), (5, 9), (0, 6), (6, 10), (1, 4), (3, 8), (8, 12), (2, 13)\}$

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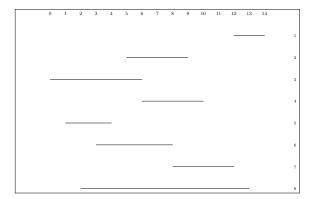
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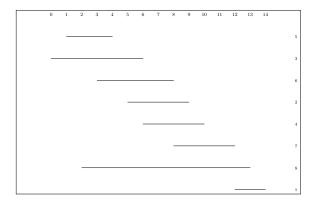
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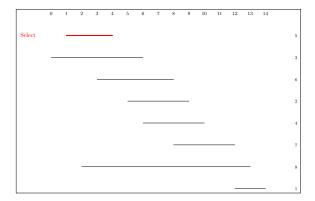
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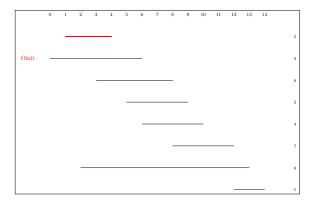
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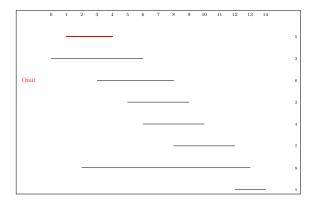
[Kleinberg-Tardos] Jon Kleinberg and Éva Tardos, Algorithm Design, Addison-Wesley, 2006.

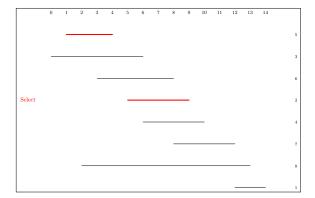


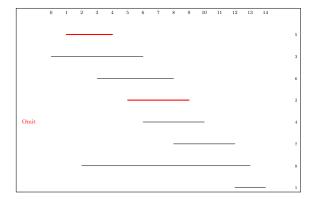


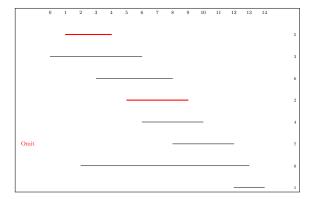


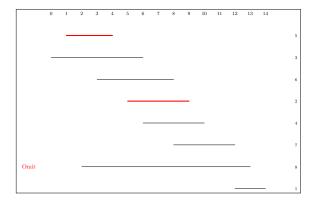


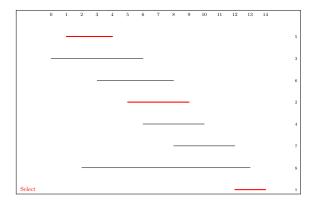


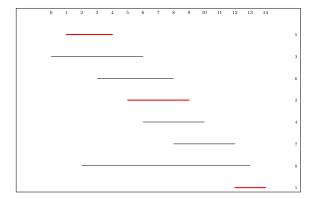


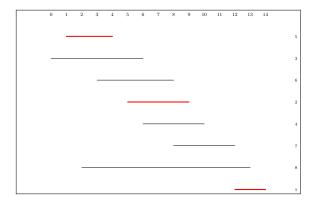












Choose 3 jobs: 5, 2, and 1

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 - If the answer is no (which it often is), seeing why the greedy approach fails may give you some insight into the structure of the problem.