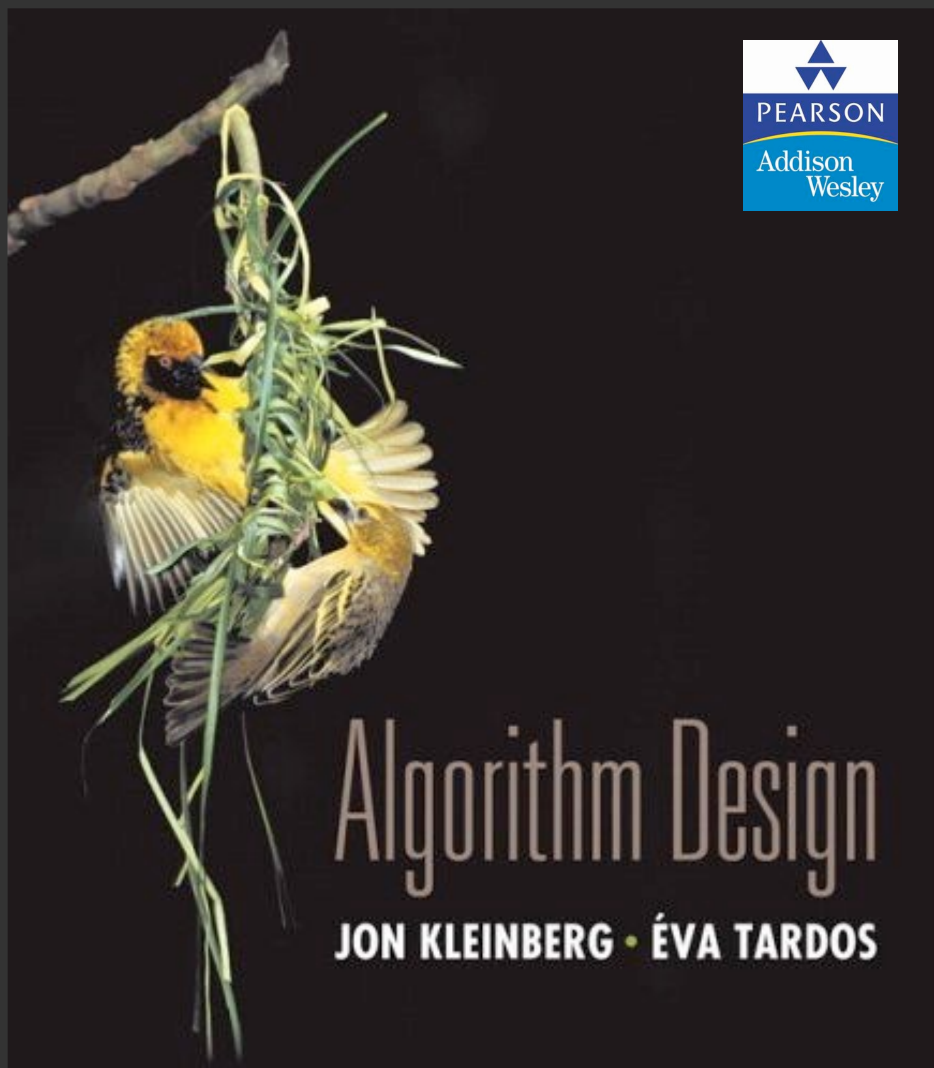


Lecture slides by Kevin Wayne

http://www.cs.princeton.edu/~wayne/kleinberg-tardos

11. Approximation Algorithms

- *load balancing*
- *center selection*
- *pricing method: vertex cover*
- *LP rounding: vertex cover*
- *generalized load balancing*
- *knapsack problem*

Last updated on 2/3/16 9:20 AM

Coping with NP-completeness

Q. Suppose I need to solve an **NP**-hard problem. What should I do?

A. Sacrifice one of three desired features.

i. Solve arbitrary instances of the problem.

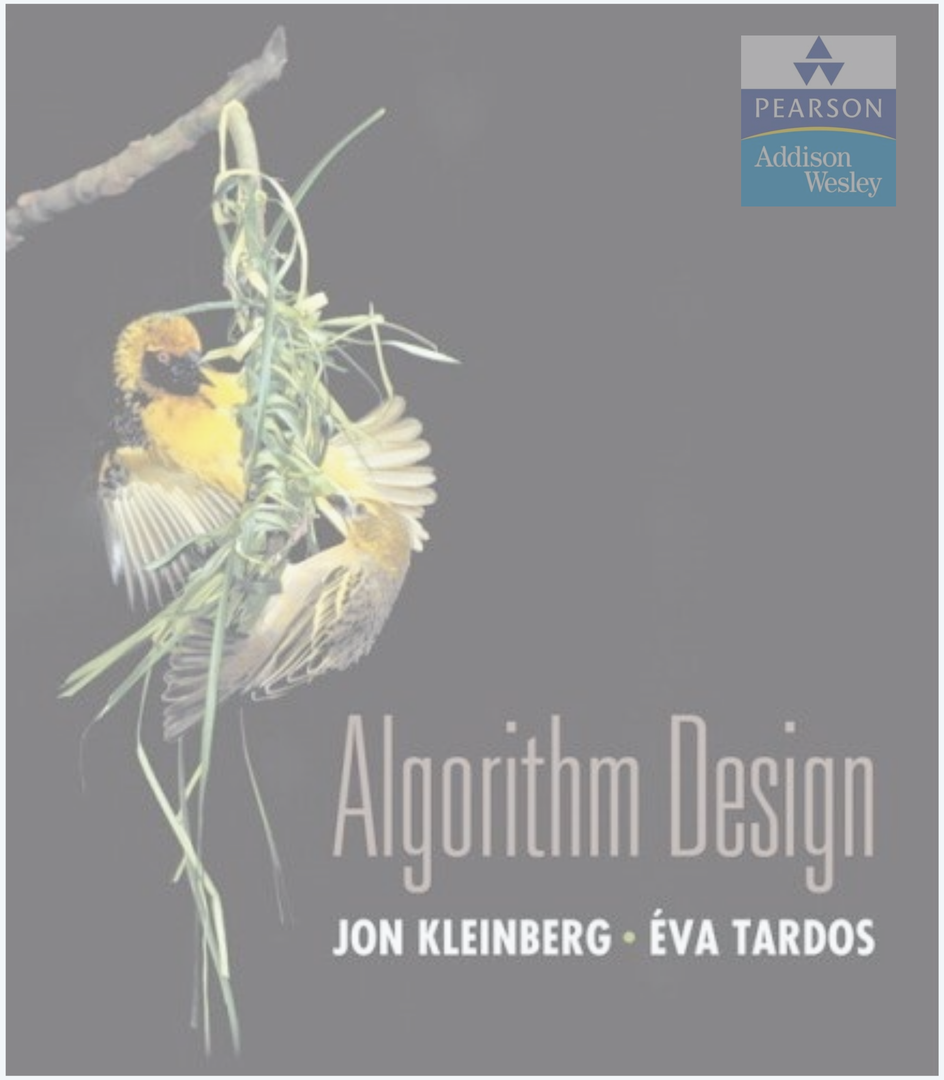
ii. Solve problem to optimality.

iii. Solve problem in polynomial time.

ρ-approximation algorithm.

- Guaranteed to run in poly-time.
- Guaranteed to solve arbitrary instance of the problem
- Guaranteed to find solution within ratio ρ of true optimum.

Challenge. Need to prove a solution's value is close to optimum, without even knowing what optimum value is



11. Approximation Algorithms

- *load balancing*
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- *knapsack problem*

Load balancing

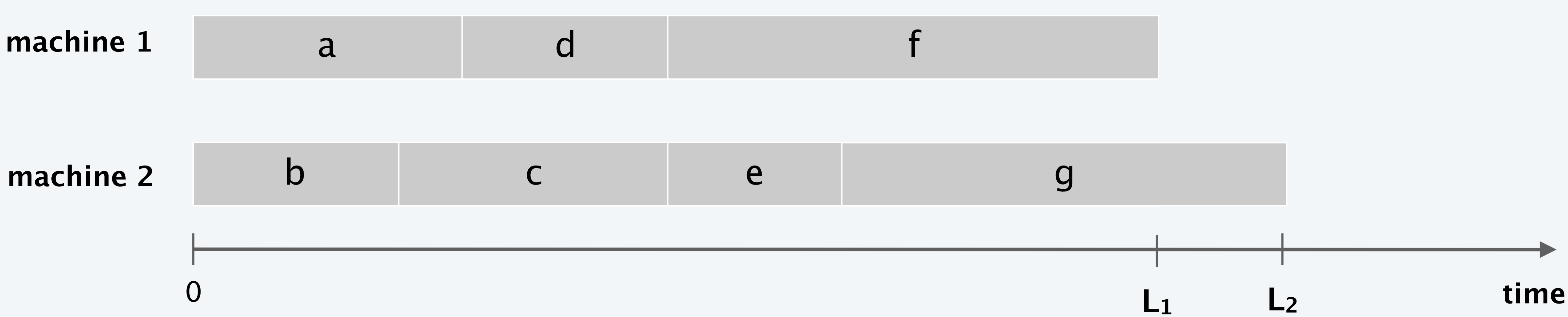
Input. m identical machines; n jobs, job j has processing time t_j.

- Job j must run contiguously on one machine.
- A machine can process at most one job at a time.

Def. Let $J(i)$ be the subset of jobs assigned to machine i.
The load of machine i is $L_i = \Sigma_{j \in J(i)} \, t_j$.

Def. The makespan is the maximum load on any machine $L = \max_i L_i$.

Load balancing. Assign each job to a machine to minimize makespan.

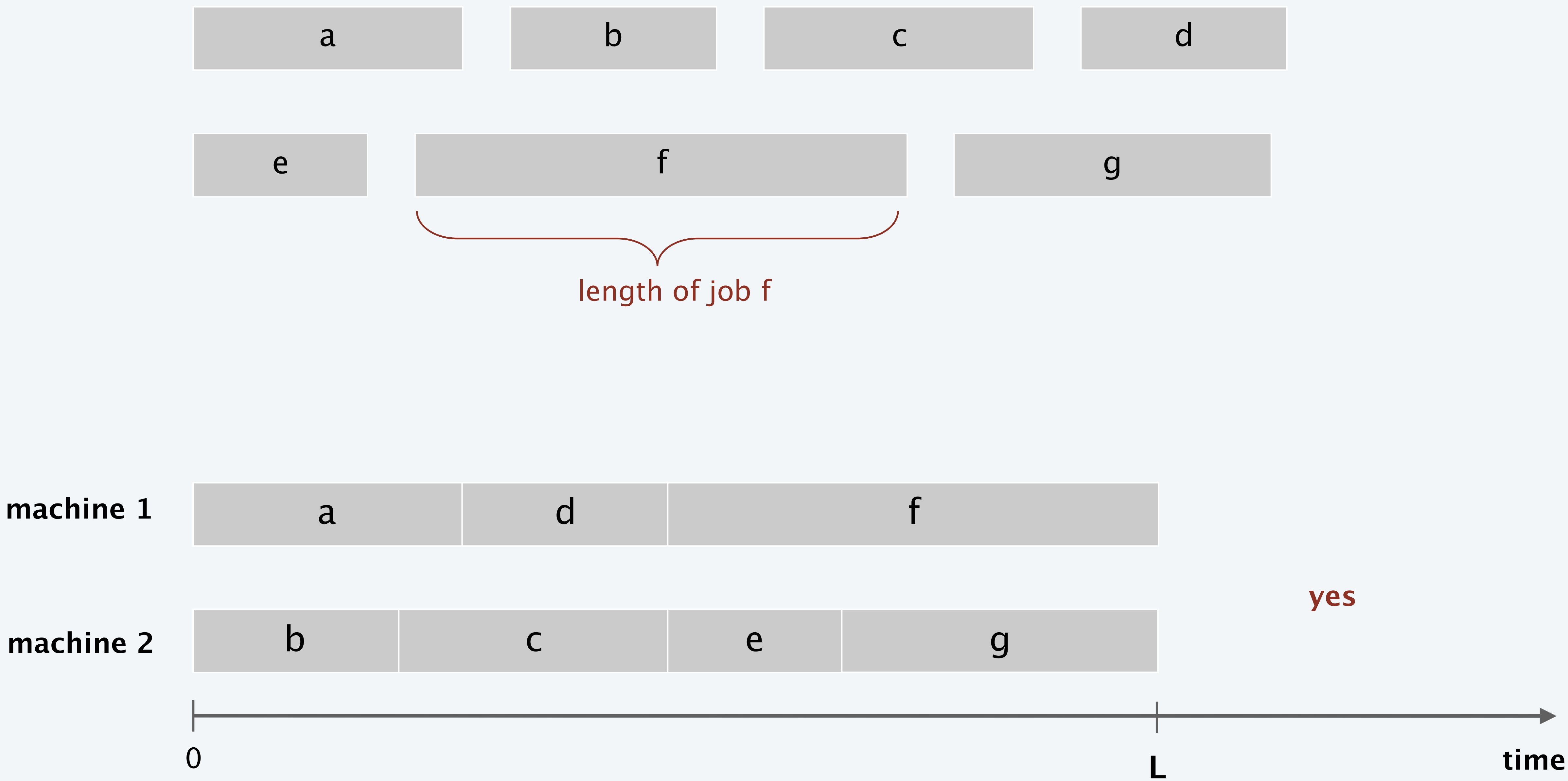


Load balancing on 2 machines is NP-hard

Claim. Load balancing is hard even if only 2 machines.

Pf. NUMBER-PARTITIONING $\leq_P$ LOAD-BALANCE.

NP-complete by Exercise 8.26



Load balancing: list scheduling

List-scheduling algorithm.

- Consider n jobs in some fixed order.
- Assign job j to machine whose load is smallest so far.

```
List-Scheduling(m, n, t₁,t₂,…,tₙ) {
   for i = 1 to m {
      Lᵢ ← 0            ← load on machine i
      J(i) ← ∅          ← jobs assigned to machine i
   }

   for j = 1 to n {
      i = argminₖ Lₖ          ← machine i has smallest load
      J(i) ← J(i) ∪ {j}       ← assign job j to machine i
      Lᵢ ← Lᵢ + tⱼ            ← update load of machine i
   }
   return J(1), …, J(m)
}
```

Implementation. $O(n \log m)$ using a priority queue.

Load balancing: list scheduling analysis

Theorem. [Graham 1966] Greedy algorithm is a 2-approximation.

- First worst-case analysis of an approximation algorithm.
- Need to compare resulting solution with optimal makespan L^*.

Lemma 1. The optimal makespan $L^* \geq \max_j t_j$.

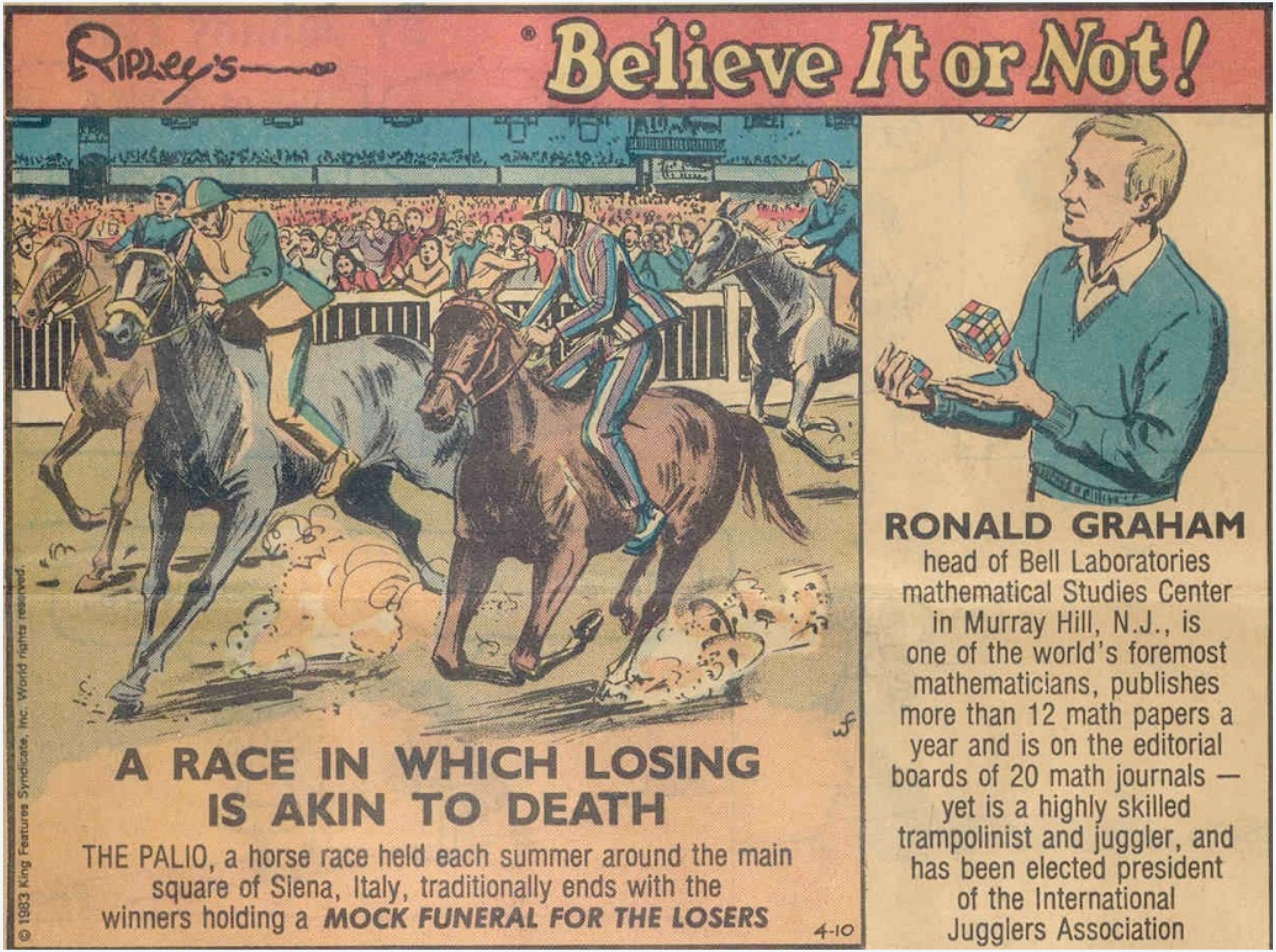
Pf. Some machine must process the most time-consuming job. ▪

Lemma 2. The optimal makespan $L^* \geq \frac{1}{m} \sum_j t_j$.

Pf.

- The total processing time is $\Sigma_j t_j$.
- One of m machines must do at least a $1 / m$ fraction of total work. ▪

Believe it or not

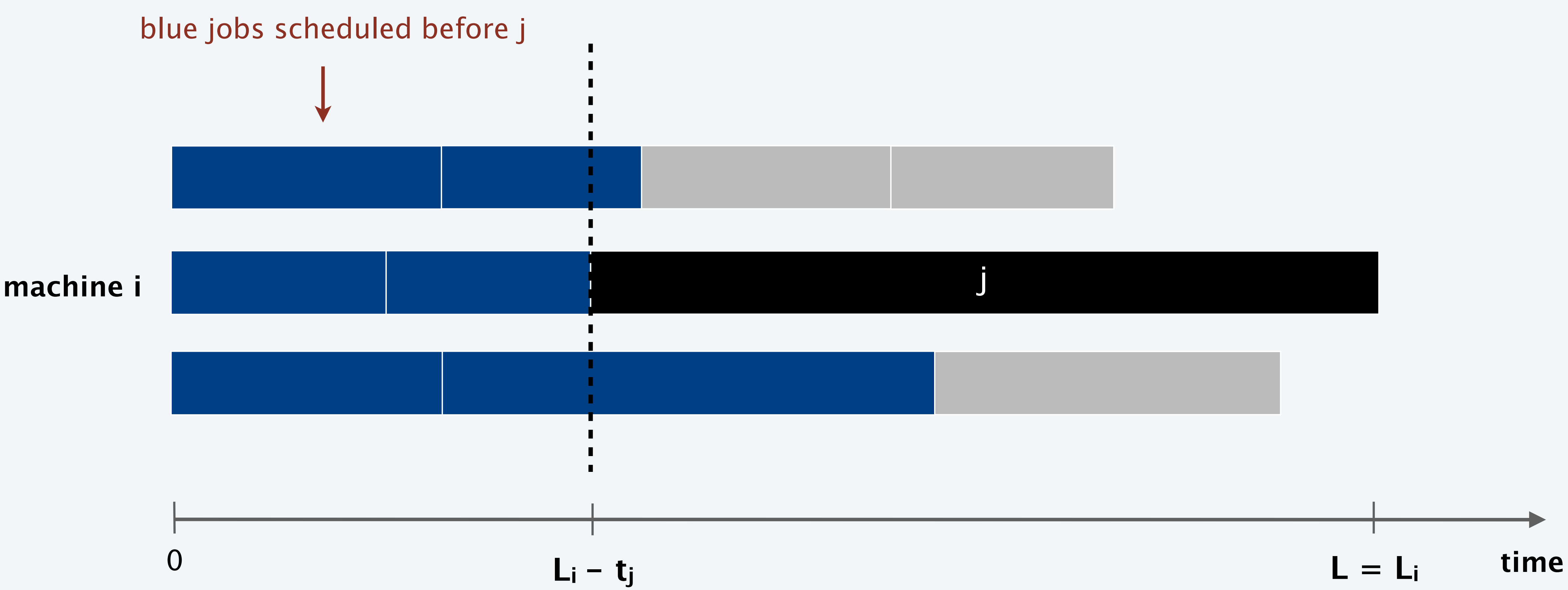


Load balancing: list scheduling analysis

Theorem. Greedy algorithm is a 2-approximation.

Pf. Consider load L_i of bottleneck machine i.

- Let j be last job scheduled on machine i.
- When job j assigned to machine i, i had smallest load.
  Its load before assignment is $L_i - t_j \;\Rightarrow\; L_i - t_j \le L_k$ for all $1 \le k \le m$.



Load balancing: list scheduling analysis

Theorem. Greedy algorithm is a 2-approximation.

Pf. Consider load L_i of bottleneck machine i.

- Let j be last job scheduled on machine i.
- When job j assigned to machine i, i had smallest load.
  Its load before assignment is $L_i - t_j \Rightarrow L_i - t_j \leq L_k$ for all $1 \leq k \leq m$.
- Sum inequalities over all k and divide by m:

$$\begin{aligned} L_i - t_j &\leq \tfrac{1}{m} \textstyle\sum_k L_k \\ &= \tfrac{1}{m} \textstyle\sum_k t_k \\ \text{Lemma 2} \longrightarrow \quad &\leq L^* \end{aligned}$$

- Now $L_i = \underbrace{(L_i - t_j)}_{\leq L^*} + \underbrace{t_j}_{\leq L^*} \leq 2L^*$. ▪

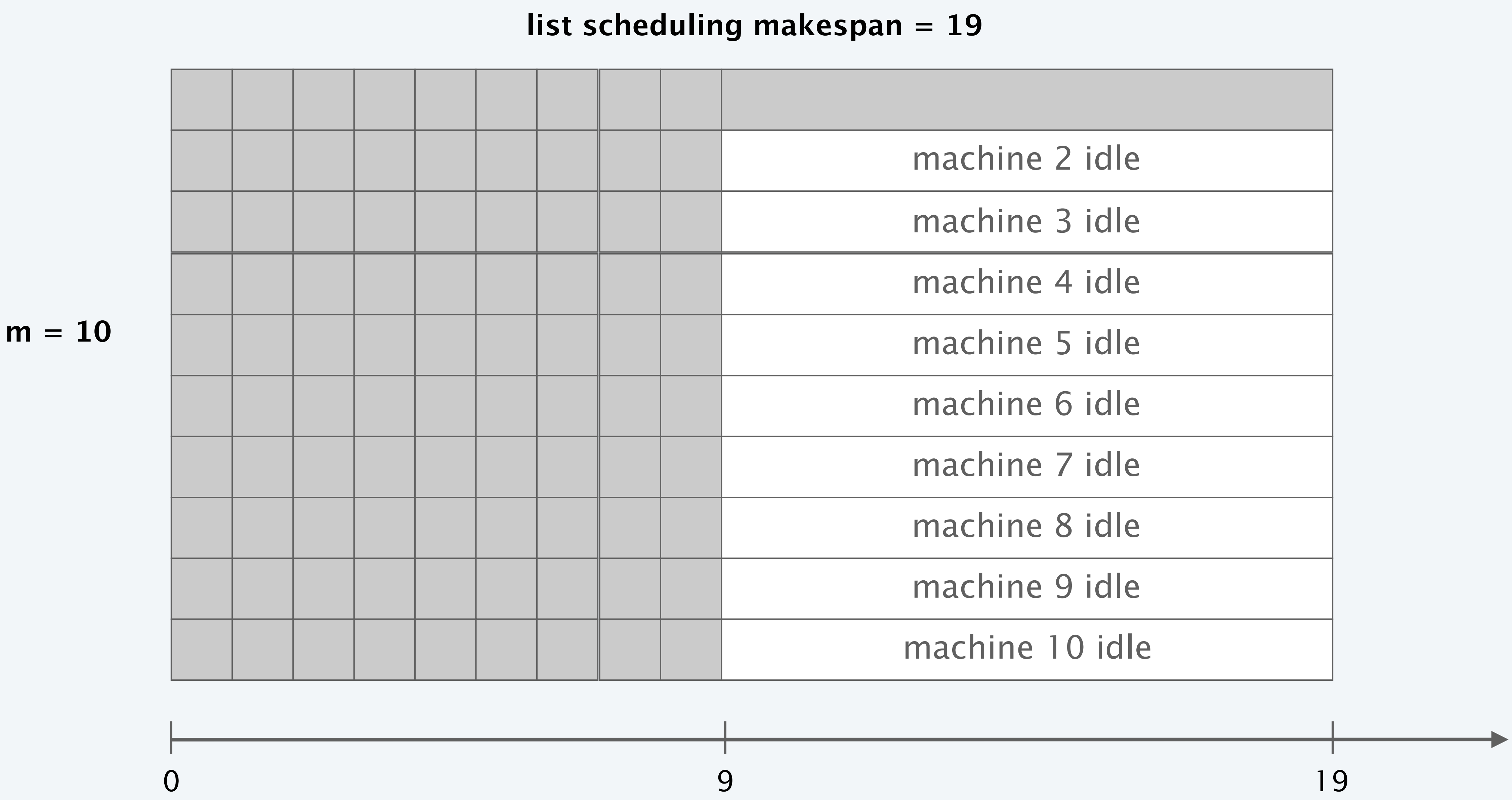
Lemma 1

Load balancing: list scheduling analysis

Q. Is our analysis tight?

A. Essentially yes.

Ex: m machines, $m\,(m-1)$ jobs length 1 jobs, one job of length m.



Load balancing: list scheduling analysis

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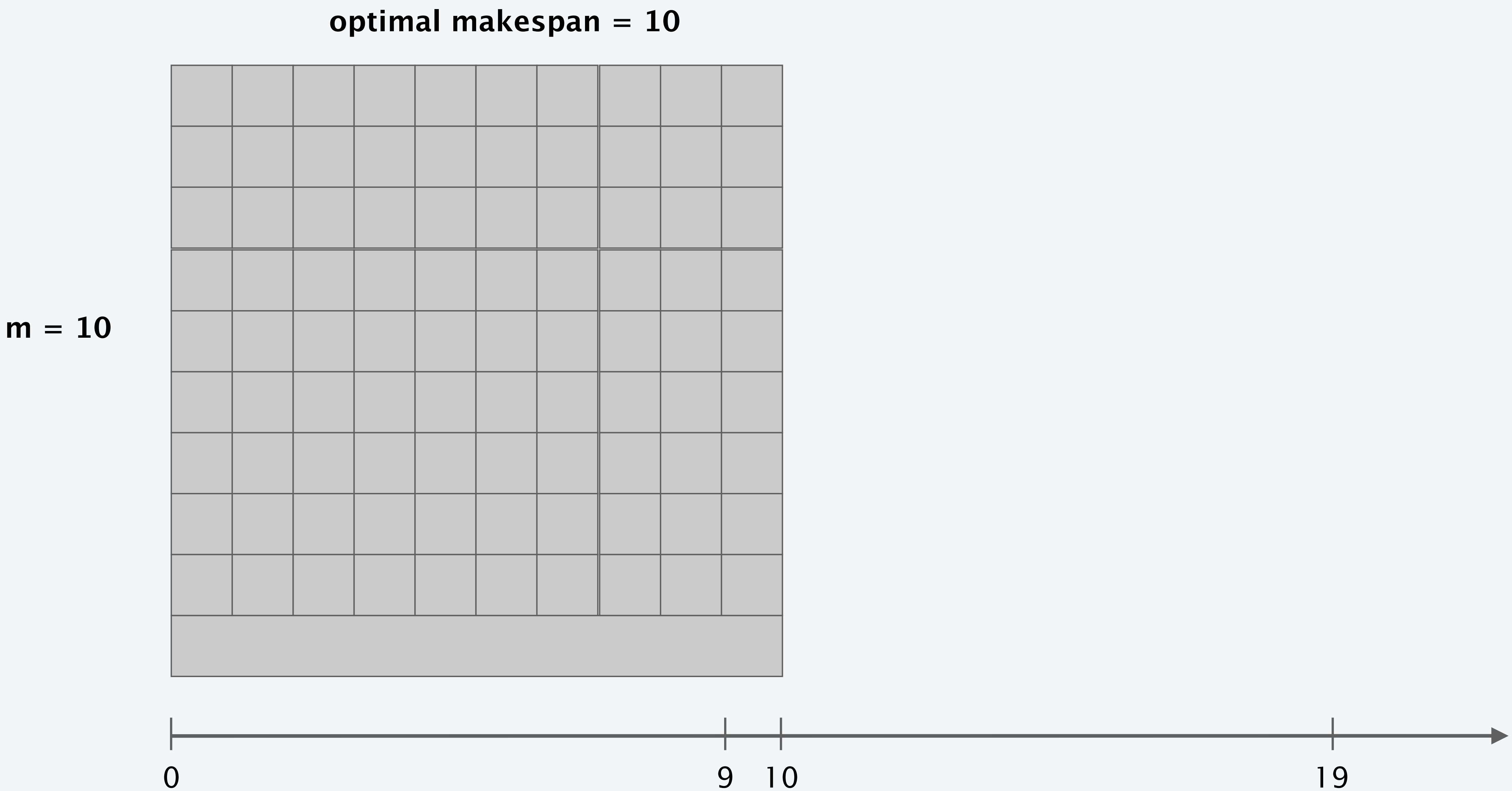


Load balancing: LPT rule

Longest processing time (LPT). Sort n jobs in descending order of processing time, and then run list scheduling algorithm.

```
LPT-List-Scheduling(m, n, t1,t2,…,tn) {
   Sort jobs so that t1 ≥ t2 ≥  … ≥ tn

   for i = 1 to m {
      Li ← 0                ← load on machine i
      J(i) ← ∅              ← jobs assigned to machine i
   }

   for j = 1 to n {
      i = argmink Lk             ← machine i has smallest load
      J(i) ← J(i) ∪ {j}          ← assign job j to machine i
      Li ← Li + tj               ← update load of machine i
   }
   return J(1), …, J(m)
}
```

Load balancing: LPT rule

Observation. If at most m jobs, then list-scheduling is optimal.

Pf. Each job put on its own machine. ▪

Lemma 3. If there are more than m jobs, $L^* \geq 2\, t_{m+1}$.

Pf.

- Consider first $m+1$ jobs $t_1, \ldots, t_{m+1}$.
- Since the t_i's are in descending order, each takes at least t_{m+1} time.
- There are $m + 1$ jobs and m machines, so by pigeonhole principle, at least one machine gets two jobs. ▪

Theorem. LPT rule is a 3/2-approximation algorithm.

Pf. Same basic approach as for list scheduling.

$$L_i = \underbrace{(L_i - t_j)}_{\leq L^*} + \underbrace{t_j}_{\leq \frac{1}{2} L^*} \leq \frac{3}{2} L^* . \qquad ▪$$

Lemma 3
(by observation, can assume number of jobs > m)

Load Balancing: LPT rule

Q. Is our 3/2 analysis tight?

A. No.

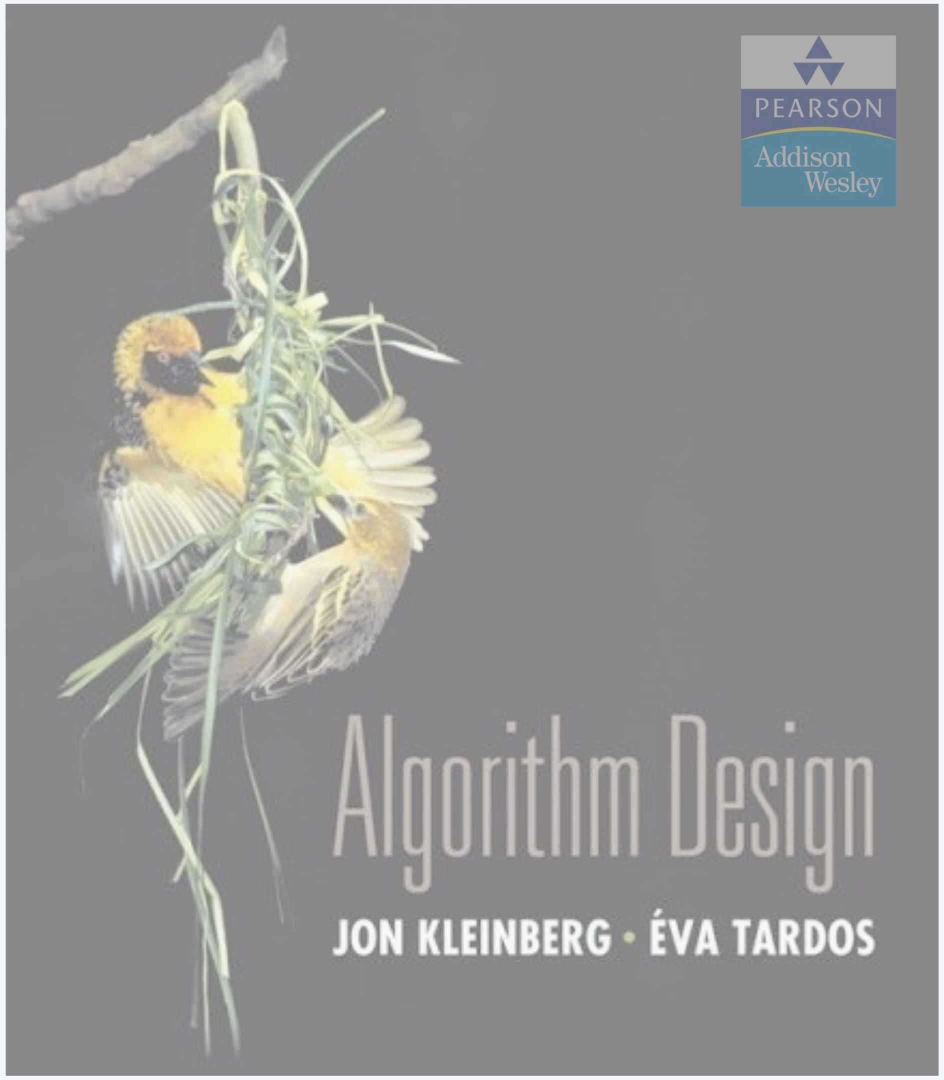
Theorem. [Graham 1969] LPT rule is a 4/3-approximation.

Pf. More sophisticated analysis of same algorithm.

Q. Is Graham's 4/3 analysis tight?

A. Essentially yes.

Ex: m machines, $n = 2m + 1$ jobs, 2 jobs of length $m, m+1, \ldots, 2m-1$ and one more job of length m.



11. Approximation Algorithms

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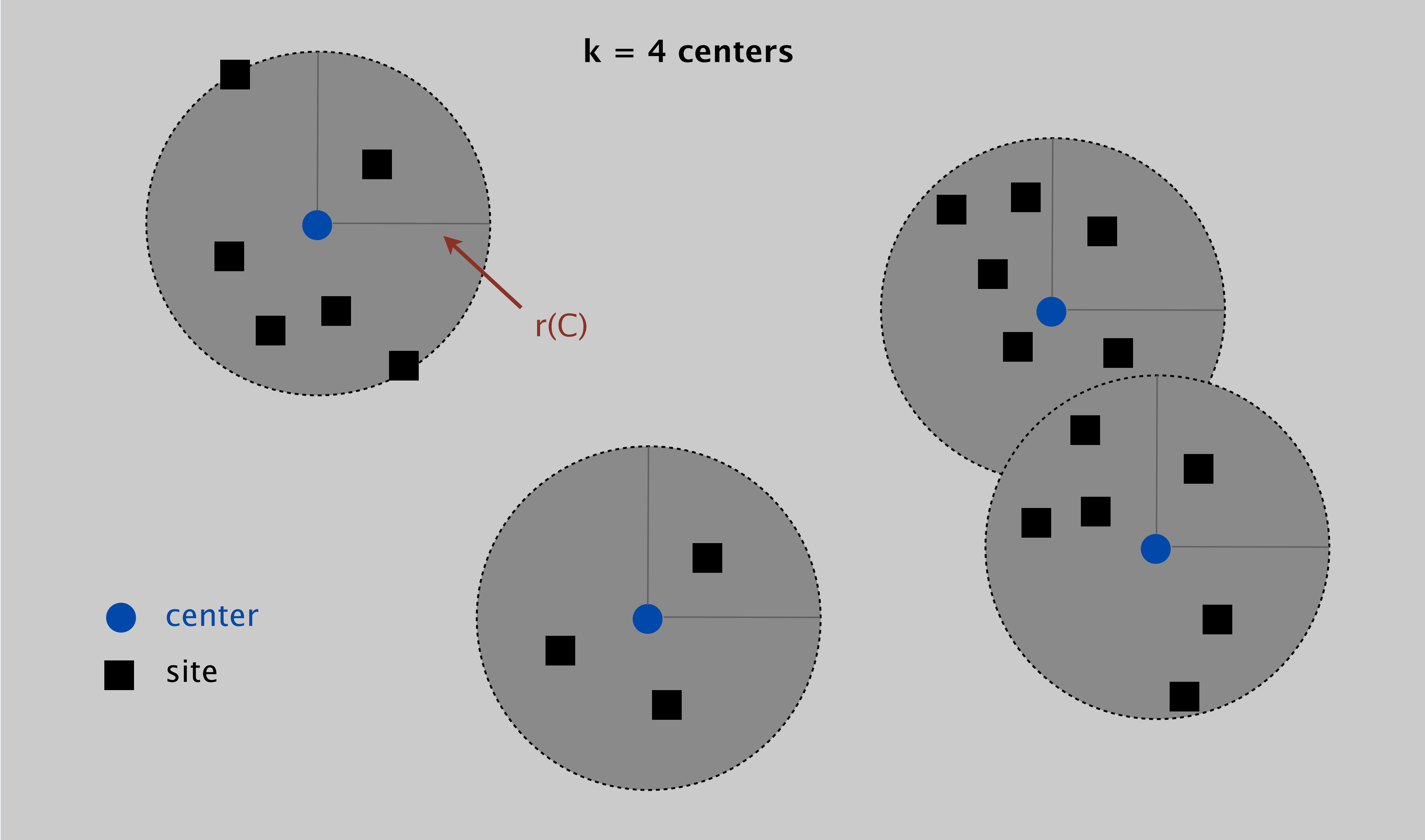
Center selection problem

Input. Set of n sites $s_1, \ldots, s_n$ and an integer $k > 0$.

Center selection problem. Select set of k centers C so that maximum distance $r(C)$ from a site to nearest center is minimized.



Center selection problem

Input. Set of n sites $s_1, \ldots, s_n$ and an integer $k > 0$.

Center selection problem. Select set of k centers C so that maximum distance $r(C)$ from a site to nearest center is minimized.

Notation.

- $dist(x, y)$ = distance between sites x and y.
- $dist(s_i, C) = \min_{c \in C} dist(s_i, c)$ = distance from s_i to closest center.
- $r(C) = \max_i dist(s_i, C)$ = smallest covering radius.

Goal. Find set of centers C that minimizes $r(C)$, subject to $|C| = k$.

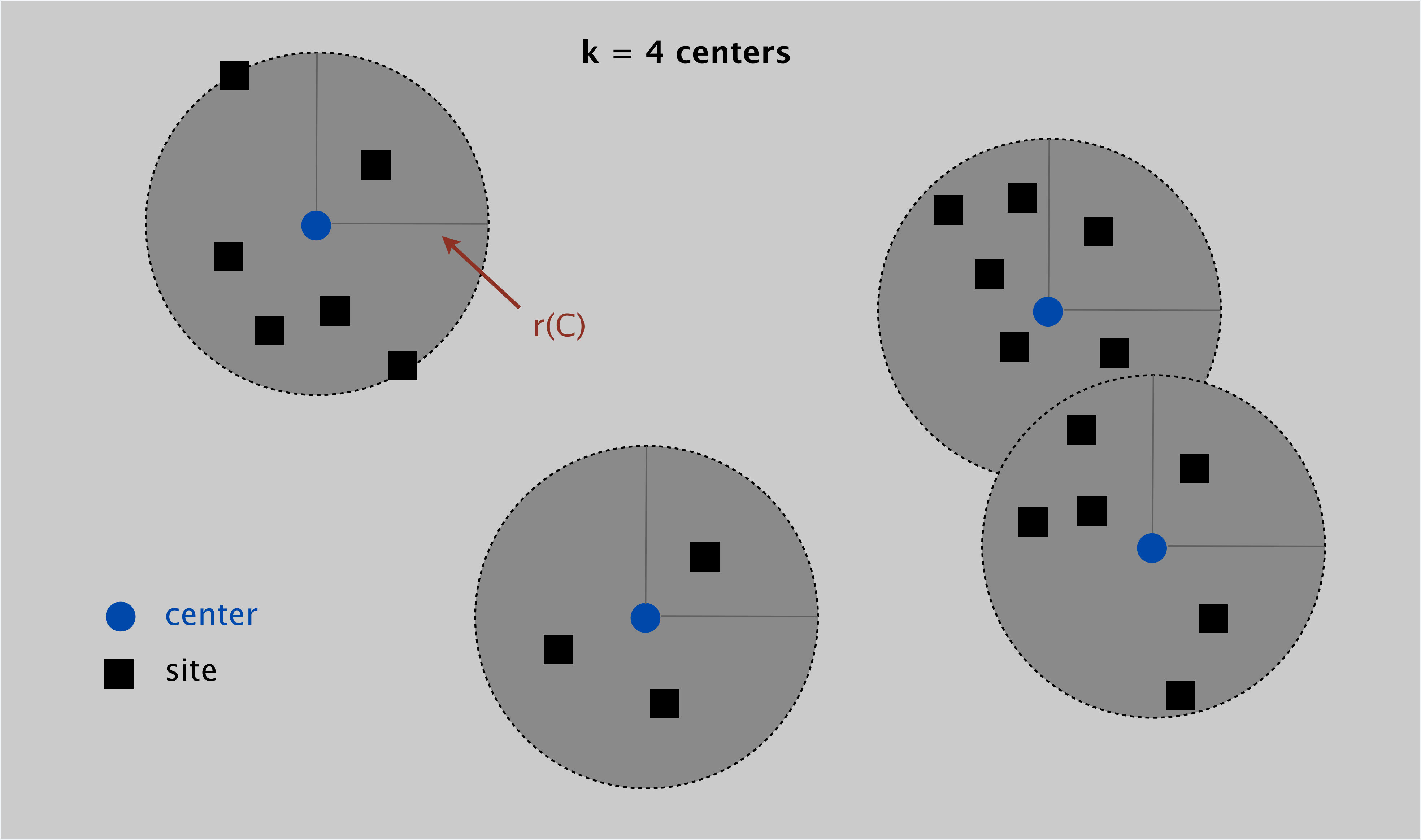
Distance function properties.

- $dist(x, x) = 0$ [identity]
- $dist(x, y) = dist(y, x)$ [symmetry]
- $dist(x, y) \leq dist(x, z) + dist(z, y)$ [triangle inequality]

Center selection example

Ex: each site is a point in the plane, a center can be any point in the plane, $dist(x, y)$ = Euclidean distance.

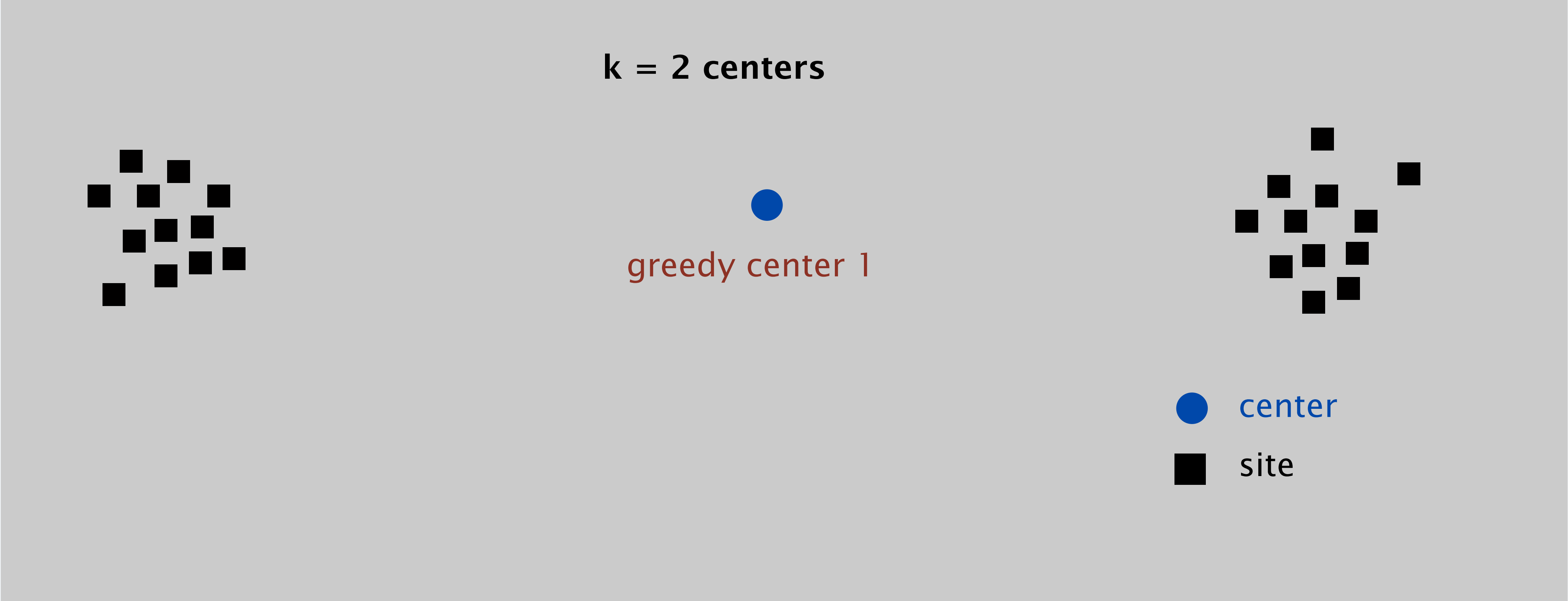
Remark: search can be infinite!



Greedy algorithm: a false start

Greedy algorithm. Put the first center at the best possible location for a single center, and then keep adding centers so as to reduce the covering radius each time by as much as possible.

Remark: arbitrarily bad!



Center selection: greedy algorithm

Repeatedly choose next center to be site farthest from any existing center.

GREEDY-CENTER-SELECTION $(k, n, s_1, s_2, \ldots, s_n)$

$C \leftarrow \varnothing$.

REPEAT k times

  Select a site s_i with maximum distance $dist(s_i, C)$.

  $C \leftarrow C \cup s_i$.

RETURN C.

site farthest from any center

Property. Upon termination, all centers in C are pairwise at least $r(C)$ apart.

Pf. By construction of algorithm.

Center selection: analysis of greedy algorithm

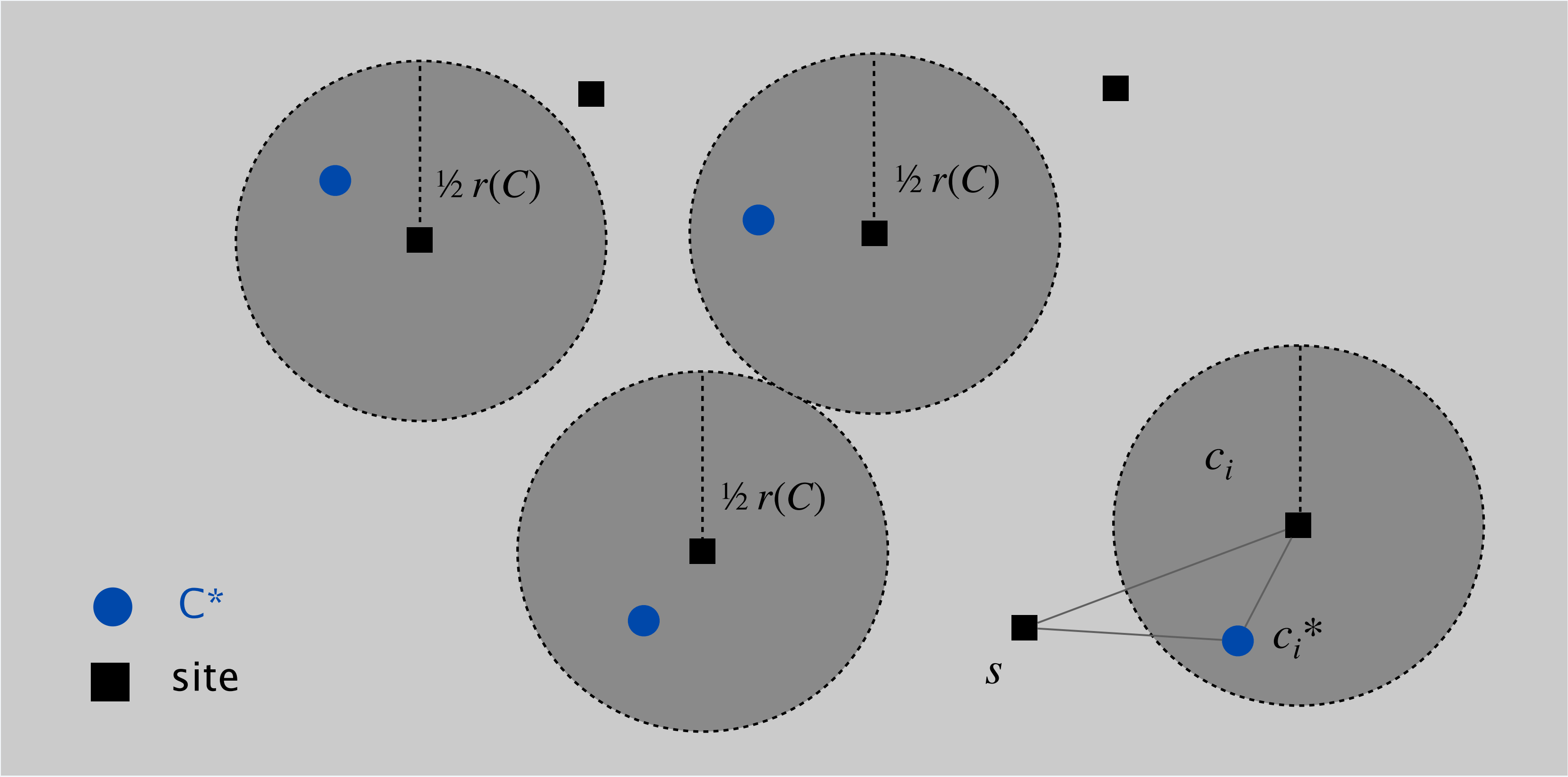
Lemma. Let C^* be an optimal set of centers. Then $r(C) \le 2r(C^*)$.

Pf. [by contradiction] Assume $r(C^*) < \frac{1}{2}\, r(C)$.

- For each site $c_i \in C$, consider ball of radius $\frac{1}{2}\, r(C)$ around it.
- Exactly one c_i^* in each ball; let c_i be the site paired with c_i^*.
- Consider any site s and its closest center $c_i^* \in C^*$.
- $dist(s, C) \le dist(s, c_i) \le dist(s, c_i^*) + dist(c_i^*, c_i) \le 2r(C^*)$.
- Thus, $r(C) \le 2r(C^*)$. ▪

≤ r(C*) since c_i* is closest center

Δ-inequality



Center selection

Lemma. Let C^* be an optimal set of centers. Then $r(C) \leq 2r(C^*)$.

Theorem. Greedy algorithm is a 2-approximation for center selection problem.

Remark. Greedy algorithm always places centers at sites, but is still within a factor of 2 of best solution that is allowed to place centers anywhere.

e.g., points in the plane

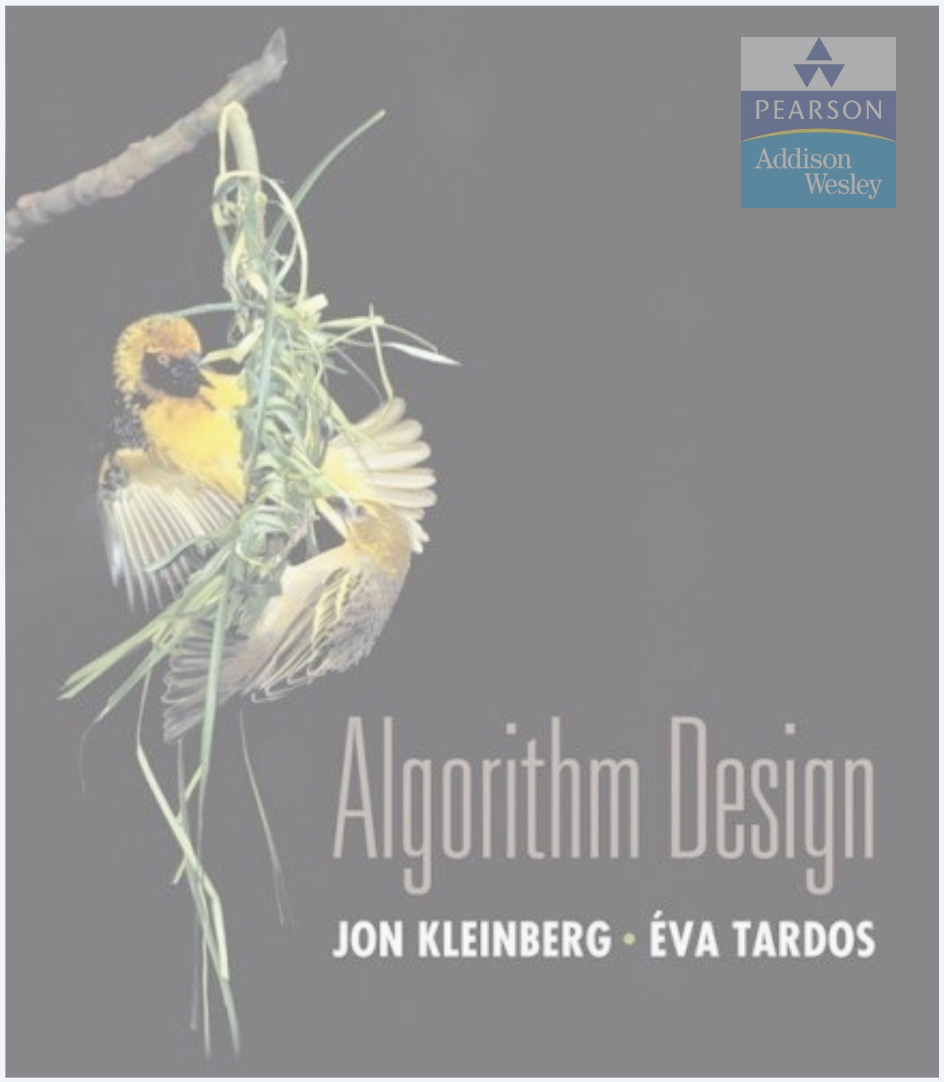
Question. Is there hope of a 3/2-approximation? 4/3?

Dominating set reduces to center selection

Theorem. Unless **P** = **NP**, there no ρ-approximation for center selection problem for any $\rho < 2$.

Pf. We show how we could use a $(2 - \varepsilon)$ approximation algorithm for CENTER-SELECTION selection to solve DOMINATING-SET in poly-time.

- Let $G = (V, E)$, k be an instance of DOMINATING-SET.
- Construct instance G' of CENTER-SELECTION with sites V and distances
  - $dist(u, v) = 1$ if $(u, v) \in E$
  - $dist(u, v) = 2$ if $(u, v) \notin E$
- Note that G' satisfies the triangle inequality.
- G has dominating set of size k iff there exists k centers C^* with $r(C^*) = 1$.
- Thus, if G has a dominating set of size k, a $(2 - \varepsilon)$-approximation algorithm for CENTER-SELECTION would find a solution C^* with $r(C^*) = 1$ since it cannot use any edge of distance 2. ▪



11. Approximation Algorithms

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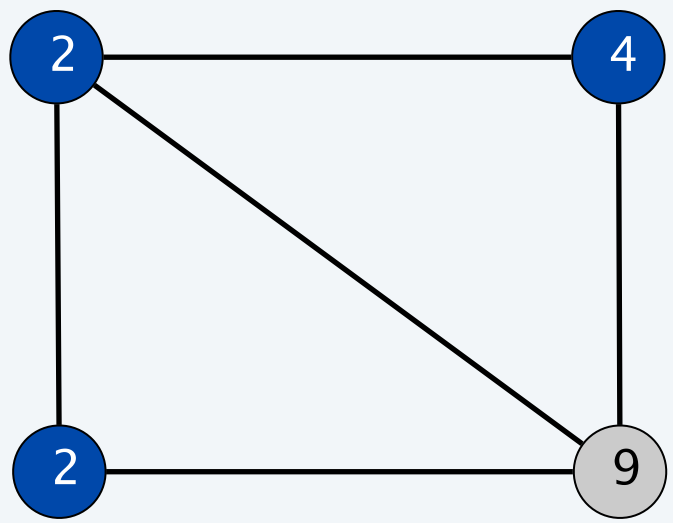
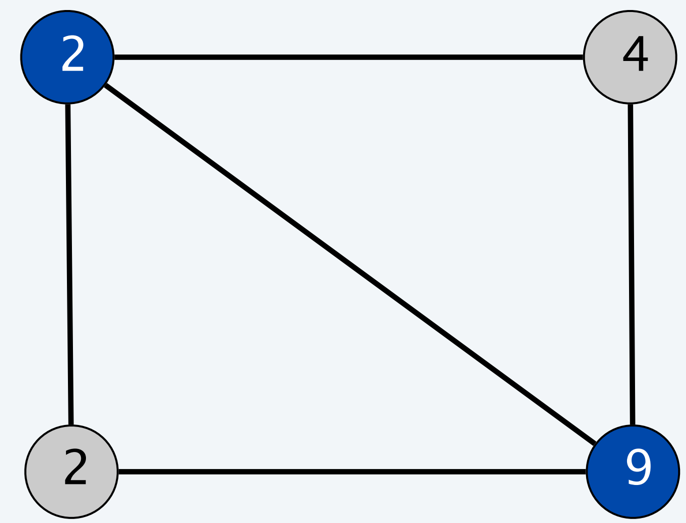
Weighted vertex cover

Definition. Given a graph $G = (V, E)$, a vertex cover is a set $S \subseteq V$ such that each edge in E has at least one end in S.

Weighted vertex cover. Given a graph G with vertex weights, find a vertex cover of minimum weight.



weight = 2 + 2 + 4



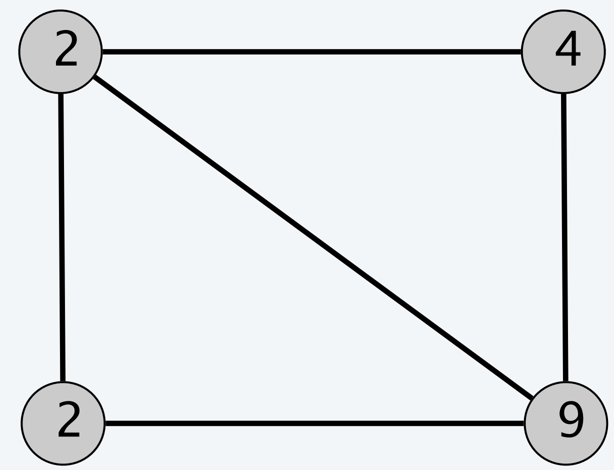
weight = 11

Pricing method

Pricing method. Each edge must be covered by some vertex.
Edge $e = (i, j)$ pays price $p_e \geq 0$ to use both vertex i and j.

Fairness. Edges incident to vertex i should pay $\leq w_i$ in total.

for each vertex i : $\sum_{e=(i,j)} p_e \leq w_i$



Fairness lemma. For any vertex cover S and any fair prices p_e : $\sum_e p_e \leq w(S)$.

Pf. $$\sum_{e \in E} p_e \leq \sum_{i \in S} \sum_{e=(i,j)} p_e \leq \sum_{i \in S} w_i = w(S). \blacksquare$$

each edge e covered by
at least one node in S

sum fairness inequalities
for each node in S

Pricing method

Set prices and find vertex cover simultaneously.

WEIGHTED-VERTEX-COVER (G, w)

$S \leftarrow \varnothing$.

FOREACH $e \in E$

$\quad p_e \leftarrow 0$.

$$\sum_{e=(i,j)} p_e = w_i$$

WHILE (there exists an edge (i, j) such that neither i nor j is tight)

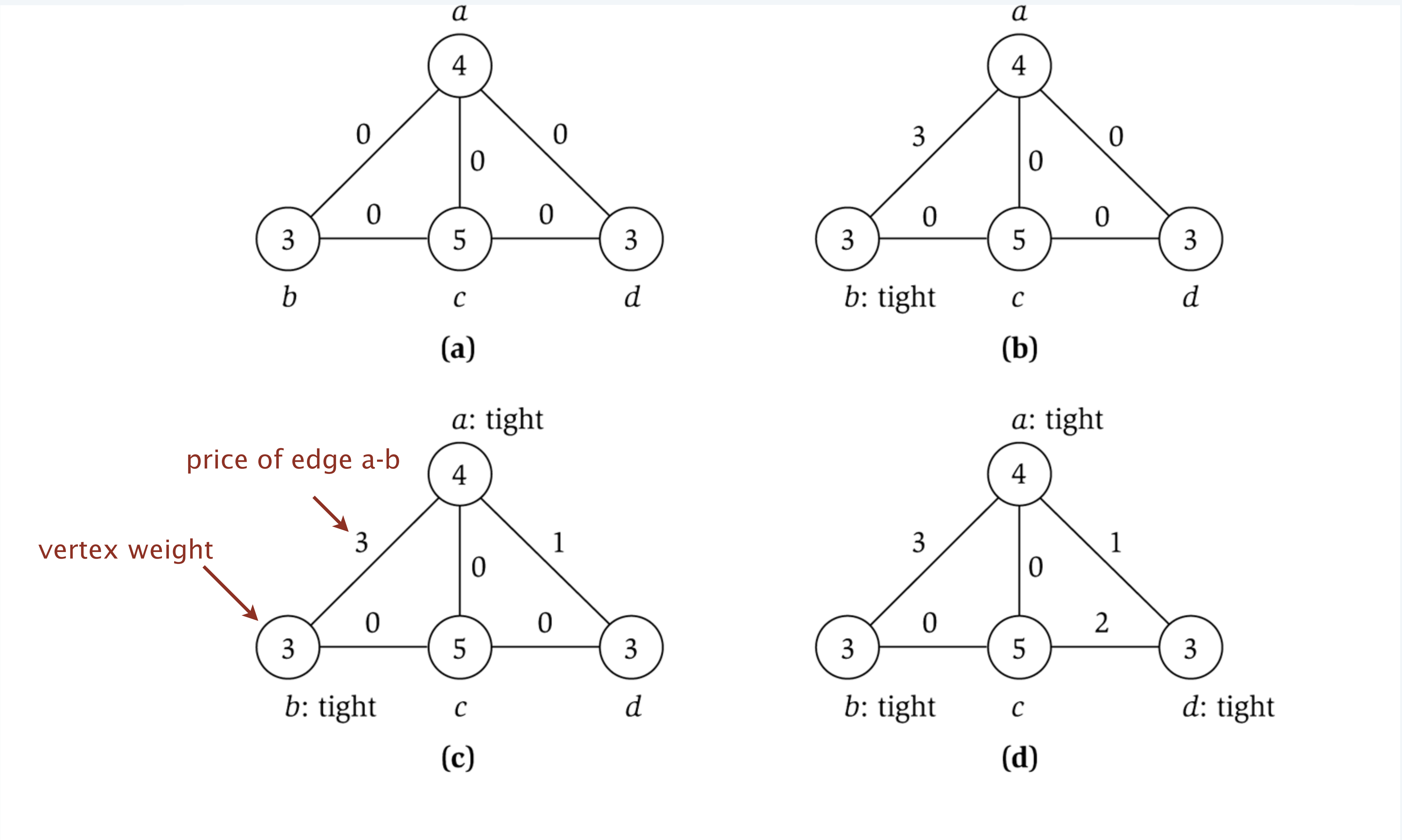
$\quad$ Select such an edge $e = (i, j)$.

$\quad$ Increase p_e as much as possible until i or j tight.

S $\leftarrow$ set of all tight nodes.

RETURN S.

Pricing method example



Pricing method: analysis

Theorem. Pricing method is a 2-approximation for WEIGHTED-VERTEX-COVER.

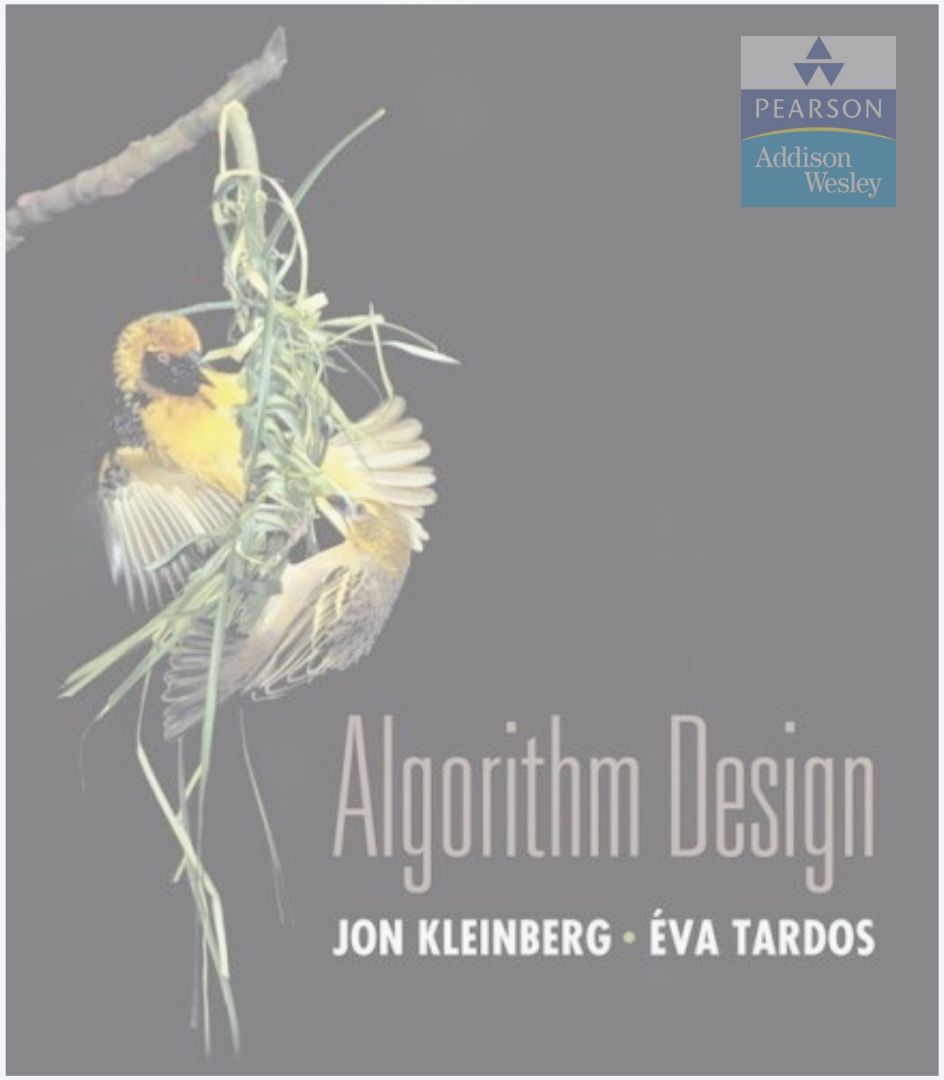
Pf.

- Algorithm terminates since at least one new node becomes tight after each iteration of while loop.

- Let S = set of all tight nodes upon termination of algorithm. S is a vertex cover: if some edge (i, j) is uncovered, then neither i nor j is tight. But then while loop would not terminate.

- Let S^* be optimal vertex cover. We show $w(S) \leq 2\, w(S^*)$.

$$w(S) = \sum_{i \in S} w_i \underset{\substack{\uparrow \\ \text{all nodes in S are tight}}}{=} \sum_{i \in S} \sum_{e=(i,j)} p_e \underset{\substack{\uparrow \\ S \subseteq V, \\ \text{prices} \geq 0}}{\leq} \sum_{i \in V} \sum_{e=(i,j)} p_e \underset{\substack{\uparrow \\ \text{each edge counted twice}}}{=} 2 \sum_{e \in E} p_e \underset{\substack{\uparrow \\ \text{fairness lemma}}}{\leq} 2w(S^*). \quad \blacksquare$$



11. APPROXIMATION ALGORITHMS

- *load balancing*
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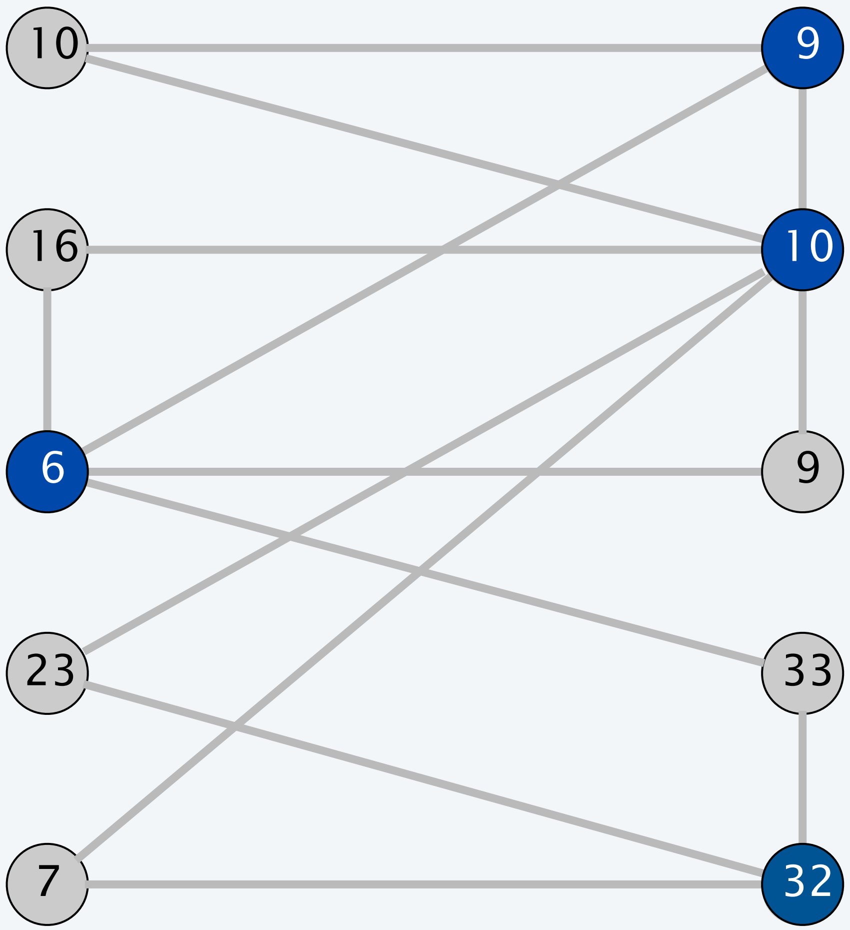
- *pricing method: vertex cover*
- *LP rounding: vertex cover*
- *generalized load balancing*
- *knapsack problem*

Weighted vertex cover

Given a graph $G = (V, E)$ with vertex weights $w_i \geq 0$, find a min weight subset of vertices $S \subseteq V$ such that every edge is incident to at least one vertex in S.



total weight = 6 + 9 + 10 + 32 = 57

Weighted vertex cover: IP formulation

Given a graph $G = (V, E)$ with vertex weights $w_i \geq 0$, find a min weight subset of vertices $S \subseteq V$ such that every edge is incident to at least one vertex in S.

Integer programming formulation.

- Model inclusion of each vertex i using a 0/1 variable x_i.

$$x_i = \begin{cases} 0 & \text{if vertex } i \text{ is not in vertex cover} \\ 1 & \text{if vertex } i \text{ is in vertex cover} \end{cases}$$

  Vertex covers in 1–1 correspondence with 0/1 assignments:
  $S = \{ i \in V : x_i = 1\}$.

- Objective function: minimize $\Sigma_i w_i x_i$.

- Must take either vertex i or j (or both): $x_i + x_j \geq 1$.

Weighted vertex cover: IP formulation

Weighted vertex cover. Integer programming formulation.

$$
\begin{array}{llll}
(ILP) \ \min & \sum_{i \in V} w_i \, x_i & & \\
\text{s. t.} & x_i + x_j & \geq \ 1 & (i,j) \in E \\
 & x_i & \in \ \{0,1\} & i \in V
\end{array}
$$

Observation. If x^* is optimal solution to (ILP), then $S = \{ i \in V : x_i^* = 1\}$ is a min weight vertex cover.

Integer programming

Given integers a_{ij}, b_i, and c_j, find integers x_j that satisfy:

$$\begin{array}{llll} \max & c^t x & & \\ \text{s. t.} & Ax & \geq & b \\ & x & & \text{integral} \end{array}$$

$$\begin{array}{rcll} \sum_{j=1}^{n} a_{ij} x_j & \geq & b_i & 1 \leq i \leq m \\ x_j & \geq & 0 & 1 \leq j \leq n \\ x_j & & \text{integral} & 1 \leq j \leq n \end{array}$$

Observation. Vertex cover formulation proves that INTEGER-PROGRAMMING is an **NP**-hard search problem.

Linear programming

Given integers a_{ij}, b_i, and c_j, find real numbers x_j that satisfy:

$$
\begin{array}{llrcl}
\text{(P)} & \max & c^t x & & \\
& \text{s. t.} & Ax & \geq & b \\
& & x & \geq & 0
\end{array}
$$

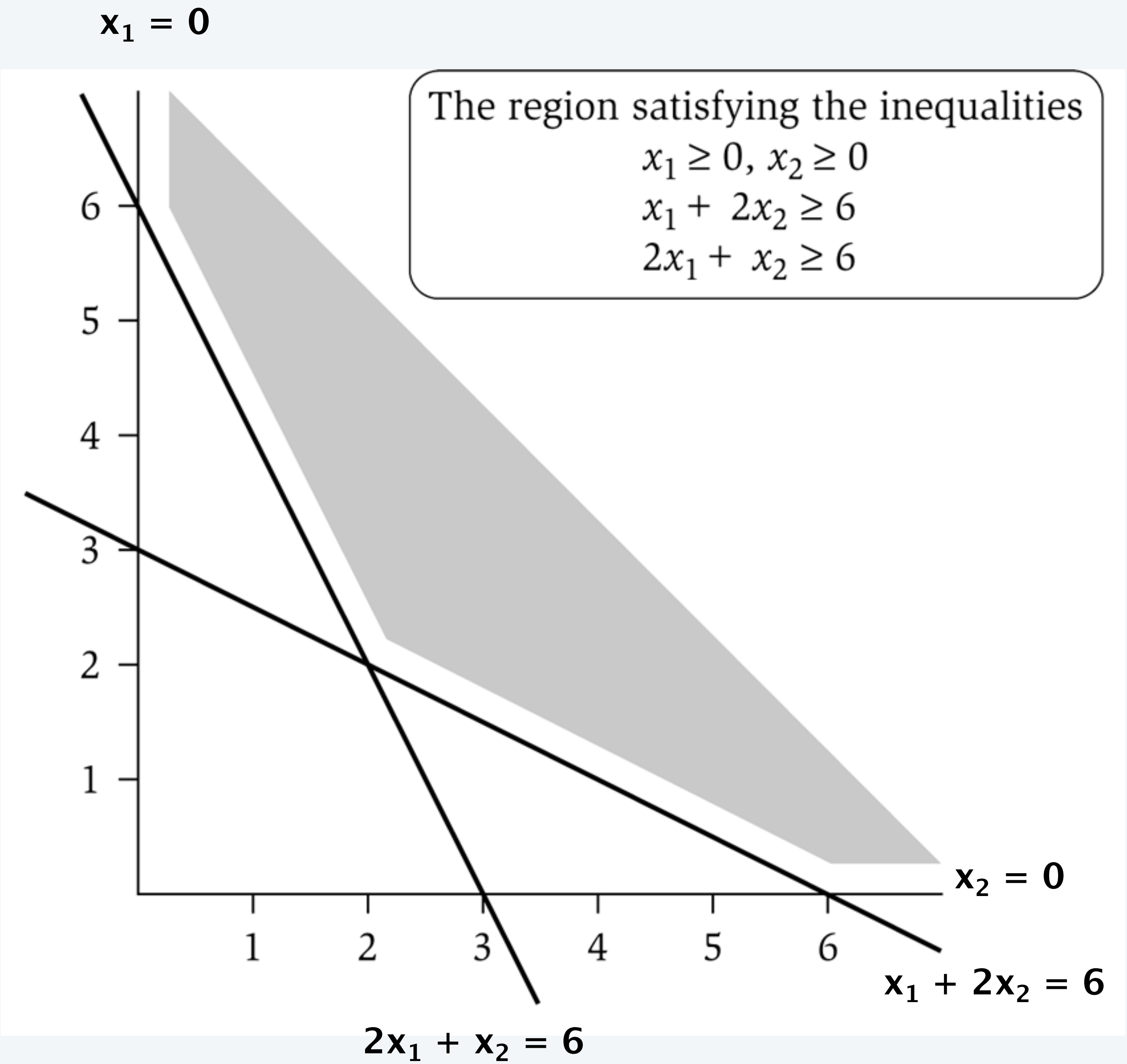
$$
\begin{array}{llrcll}
\text{(P)} & \max & \sum_{j=1}^{n} c_j x_j & & & \\
& \text{s. t.} & \sum_{j=1}^{n} a_{ij} x_j & \geq & b_i & 1 \leq i \leq m \\
& & x_j & \geq & 0 & 1 \leq j \leq n
\end{array}
$$

Linear. No x^2, xy, $arccos(x)$, $x(1-x)$, etc.

Simplex algorithm. [Dantzig 1947] Can solve LP in practice.
Ellipsoid algorithm. [Khachian 1979] Can solve LP in poly-time.

LP feasible region

LP geometry in 2D.



Weighted vertex cover: LP relaxation

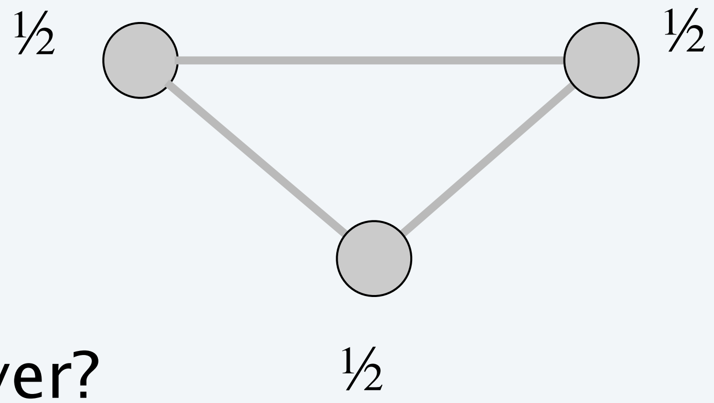
Linear programming relaxation.

$$
\begin{array}{llll}
(LP) \ \min & \displaystyle\sum_{i \in V} w_i \, x_i & & \\
\text{s. t.} & x_i + x_j & \geq 1 & (i,j) \in E \\
 & x_i & \geq 0 & i \in V
\end{array}
$$

Observation. Optimal value of (LP) is $\leq$ optimal value of (ILP).

Pf. LP has fewer constraints.

Note. LP is not equivalent to vertex cover.



Q. How can solving LP help us find a small vertex cover?

A. Solve LP and round fractional values.

Weighted vertex cover: LP rounding algorithm

Lemma. If x^* is optimal solution to (LP), then $S = \{ i \in V : x_i^* \geq ½\}$ is a vertex cover whose weight is at most twice the min possible weight.

Pf. [S is a vertex cover]

- Consider an edge $(i, j) \in E$.
- Since $x_i^* + x_j^* \geq 1$, either $x_i^* \geq ½$ or $x_j^* \geq ½$ $\Rightarrow$ (i, j) covered.

Pf. [S has desired cost]

- Let S^* be optimal vertex cover. Then

$$\sum_{i \in S^*} w_i \;\underbrace{\geq}_{\text{LP is a relaxation}}\; \sum_{i \in S} w_i\, x_i^* \;\underbrace{\geq}_{x_i^* \,\geq\, ½}\; \frac{1}{2} \sum_{i \in S} w_i$$

Theorem. The rounding algorithm is a 2-approximation algorithm.
Pf. Lemma + fact that LP can be solved in poly-time.

Weighted vertex cover inapproximability

Theorem. [Dinur-Safra 2004] If **P ≠ NP**, then no ρ-approximation for WEIGHTED-VERTEX-COVER for any $\rho < 1.3606$ (even if all weights are 1).

On the Hardness of Approximating Minimum Vertex Cover

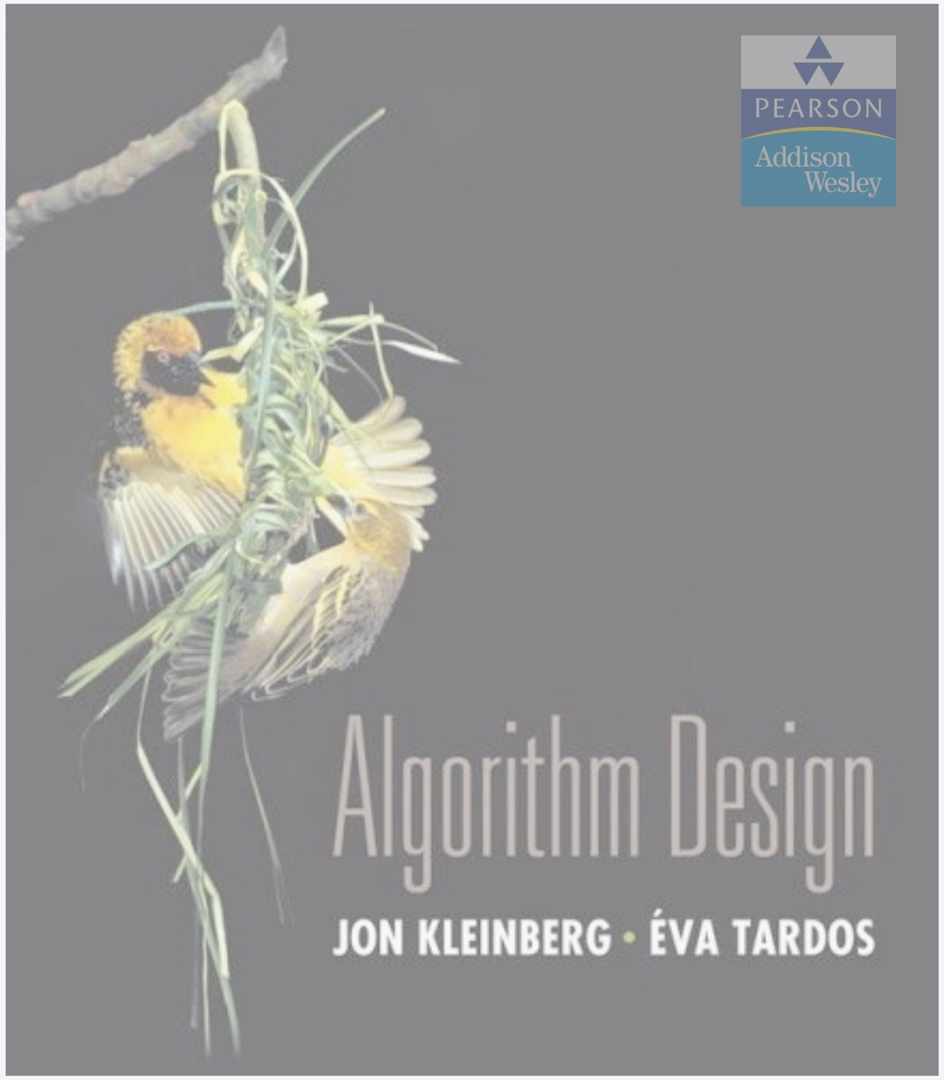
Irit Dinur* Samuel Safra†

May 26, 2004

Abstract

We prove the Minimum Vertex Cover problem to be NP-hard to approximate to within a factor of 1.3606, extending on previous PCP and hardness of approximation technique. To that end, one needs to develop a new proof framework, and borrow and extend ideas from several fields.

Open research problem. Close the gap.



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- *LP rounding: vertex cover*
- *generalized load balancing*
- *knapsack problem*

Generalized load balancing

Input. Set of m machines M; set of n jobs J.

- Job $j \in J$ must run contiguously on an authorized machine in $M_j \subseteq M$.
- Job $j \in J$ has processing time t_j.
- Each machine can process at most one job at a time.

Def. Let $J(i)$ be the subset of jobs assigned to machine i.
The load of machine i is $L_i = \Sigma_{j \in J(i)} t_j$.

Def. The makespan is the maximum load on any machine $= \max_i L_i$.

Generalized load balancing. Assign each job to an authorized machine to minimize makespan.

Generalized load balancing: integer linear program and relaxation

ILP formulation. x_{ij} = time machine i spends processing job j.

$$
\begin{array}{llcll}
(IP) & \min & L & & \\
& \text{s.t.} & \sum_i x_{ij} & = & t_j & \text{for all } j \in J \\
& & \sum_j x_{ij} & \leq & L & \text{for all } i \in M \\
& & x_{ij} & \in & \{0, t_j\} & \text{for all } j \in J \text{ and } i \in M_j \\
& & x_{ij} & = & 0 & \text{for all } j \in J \text{ and } i \notin M_j
\end{array}
$$

LP relaxation.

$$
\begin{array}{llcll}
(LP) & \min & L & & \\
& \text{s.t.} & \sum_i x_{ij} & = & t_j & \text{for all } j \in J \\
& & \sum_j x_{ij} & \leq & L & \text{for all } i \in M \\
& & x_{ij} & \geq & 0 & \text{for all } j \in J \text{ and } i \in M_j \\
& & x_{ij} & = & 0 & \text{for all } j \in J \text{ and } i \notin M_j
\end{array}
$$

Generalized load balancing: lower bounds

Lemma 1. The optimal makespan $L^* \geq \max_j t_j$.

Pf. Some machine must process the most time-consuming job. ▪

Lemma 2. Let L be optimal value to the LP. Then, optimal makespan $L^* \geq L$.

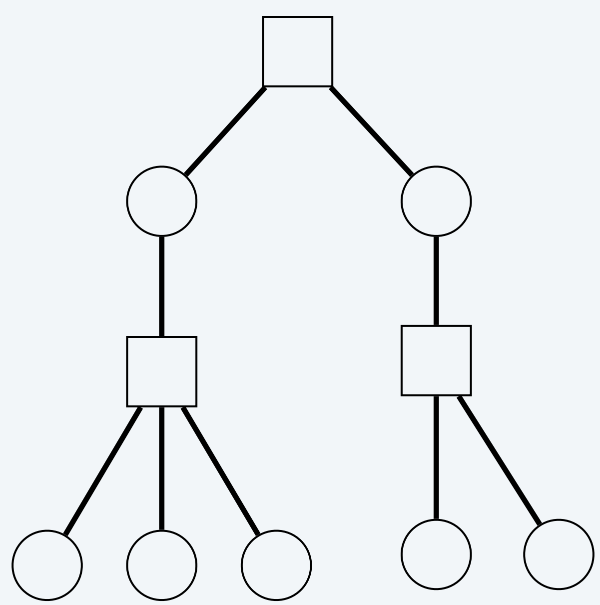
Pf. LP has fewer constraints than IP formulation. ▪

Generalized load balancing: structure of LP solution

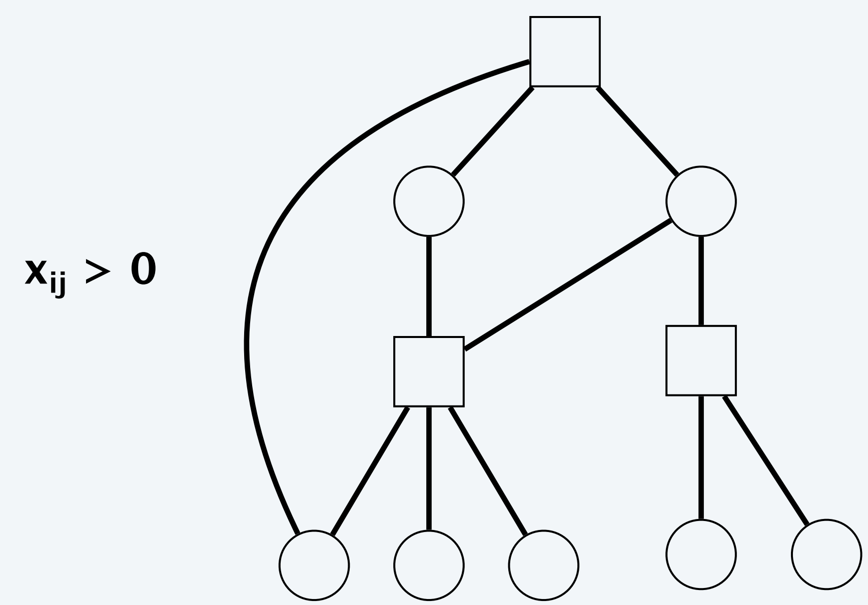
Lemma 3. Let x be solution to LP. Let $G(x)$ be the graph with an edge between machine i and job j if $x_{ij} > 0$. Then $G(x)$ is acyclic.

can transform x into another LP solution where G(x) is acyclic if LP solver doesn't return such an x

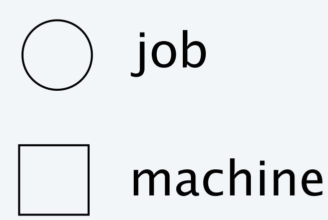
Pf. (deferred)



G(x) acyclic



G(x) cyclic

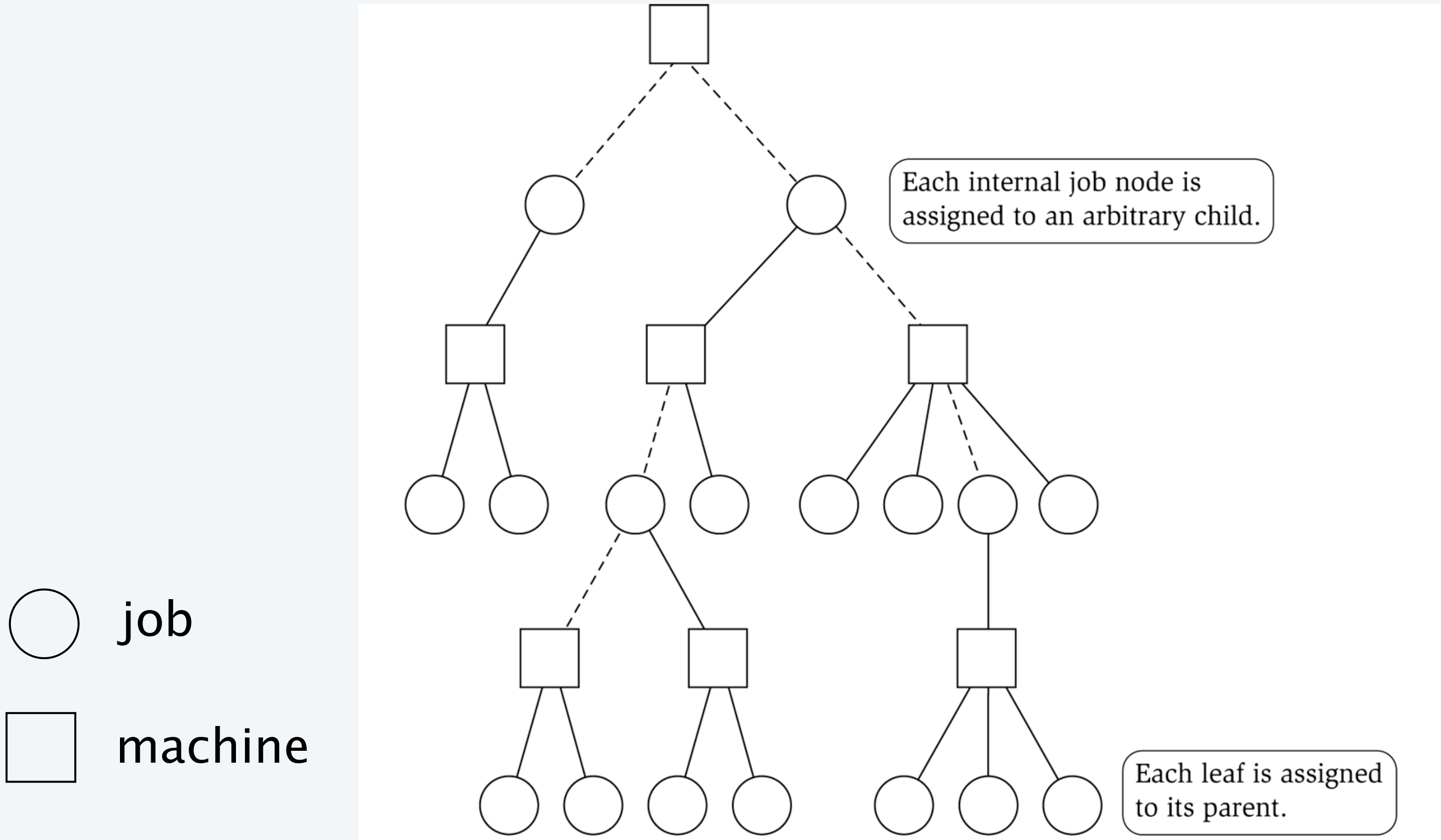


Generalized load balancing: rounding

Rounded solution. Find LP solution x where $G(x)$ is a forest. Root forest $G(x)$ at some arbitrary machine node r.

- If job j is a leaf node, assign j to its parent machine i.
- If job j is not a leaf node, assign j to any one of its children.

Lemma 4. Rounded solution only assigns jobs to authorized machines.
Pf. If job j is assigned to machine i, then $x_{ij} > 0$. LP solution can only assign positive value to authorized machines. ▪



Generalized load balancing: analysis

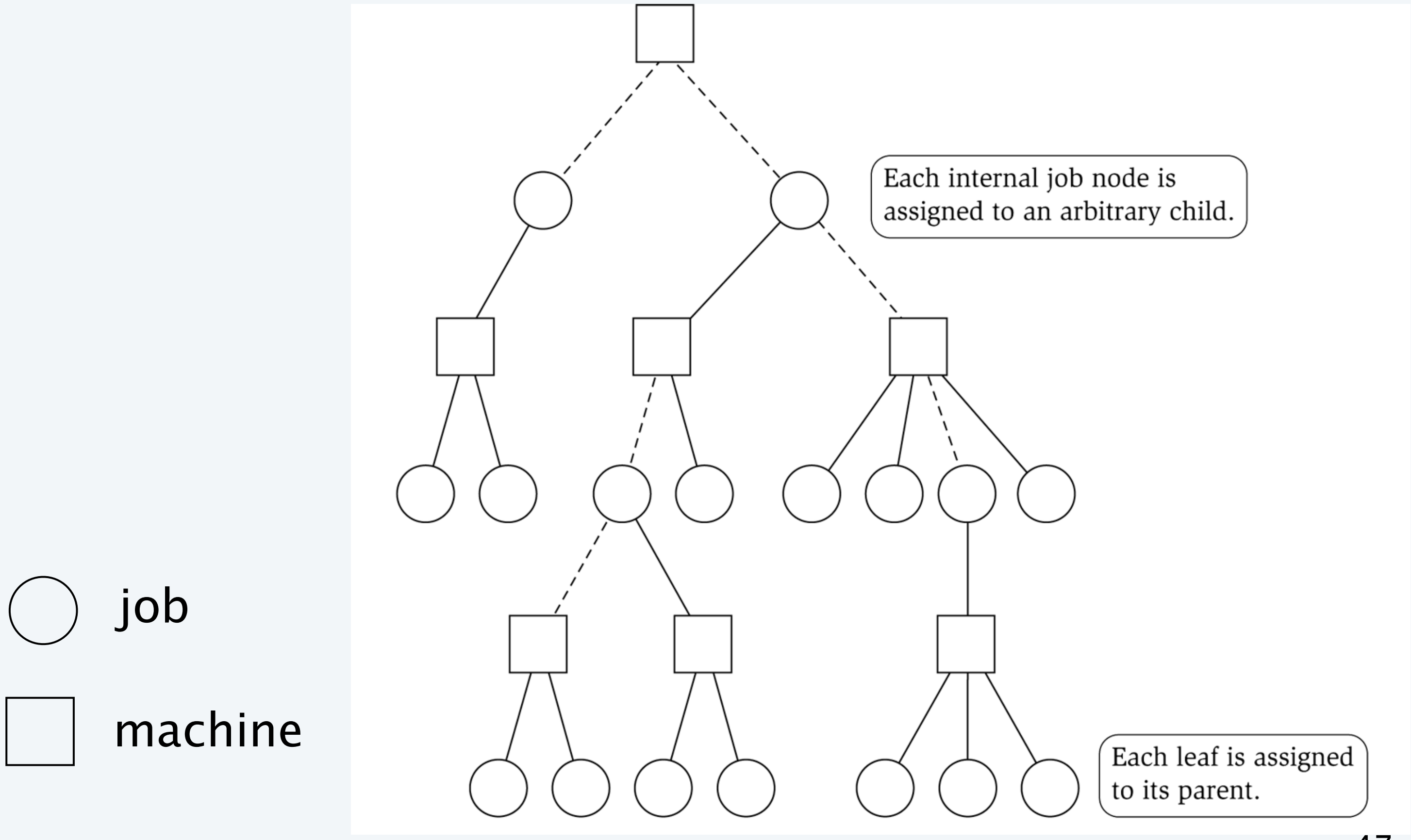
Lemma 5. If job j is a leaf node and machine $i = parent(j)$, then $x_{ij} = t_j$.

Pf.

- Since i is a leaf, $x_{ij} = 0$ for all $j \neq parent(i)$.
- LP constraint guarantees $\Sigma_i \, x_{ij} = t_j$. ▪

Lemma 6. At most one non-leaf job is assigned to a machine.

Pf. The only possible non-leaf job assigned to machine i is $parent(i)$. ▪



Generalized load balancing: analysis

Theorem. Rounded solution is a 2-approximation.

Pf.

- Let $J(i)$ be the jobs assigned to machine i.
- By Lemma 6, the load L_i on machine i has two components:
  - leaf nodes:

$$\sum_{\substack{j \in J(i) \\ j \text{ is a leaf}}} t_j \overset{\text{Lemma 5}}{=} \sum_{\substack{j \in J(i) \\ j \text{ is a leaf}}} x_{ij} \le \sum_{j \in J} x_{ij} \overset{\text{LP}}{\le} \underbrace{L}_{\text{optimal value of LP}} \overset{\text{Lemma 2 (LP is a relaxation)}}{\le} L^*$$

  - parent:

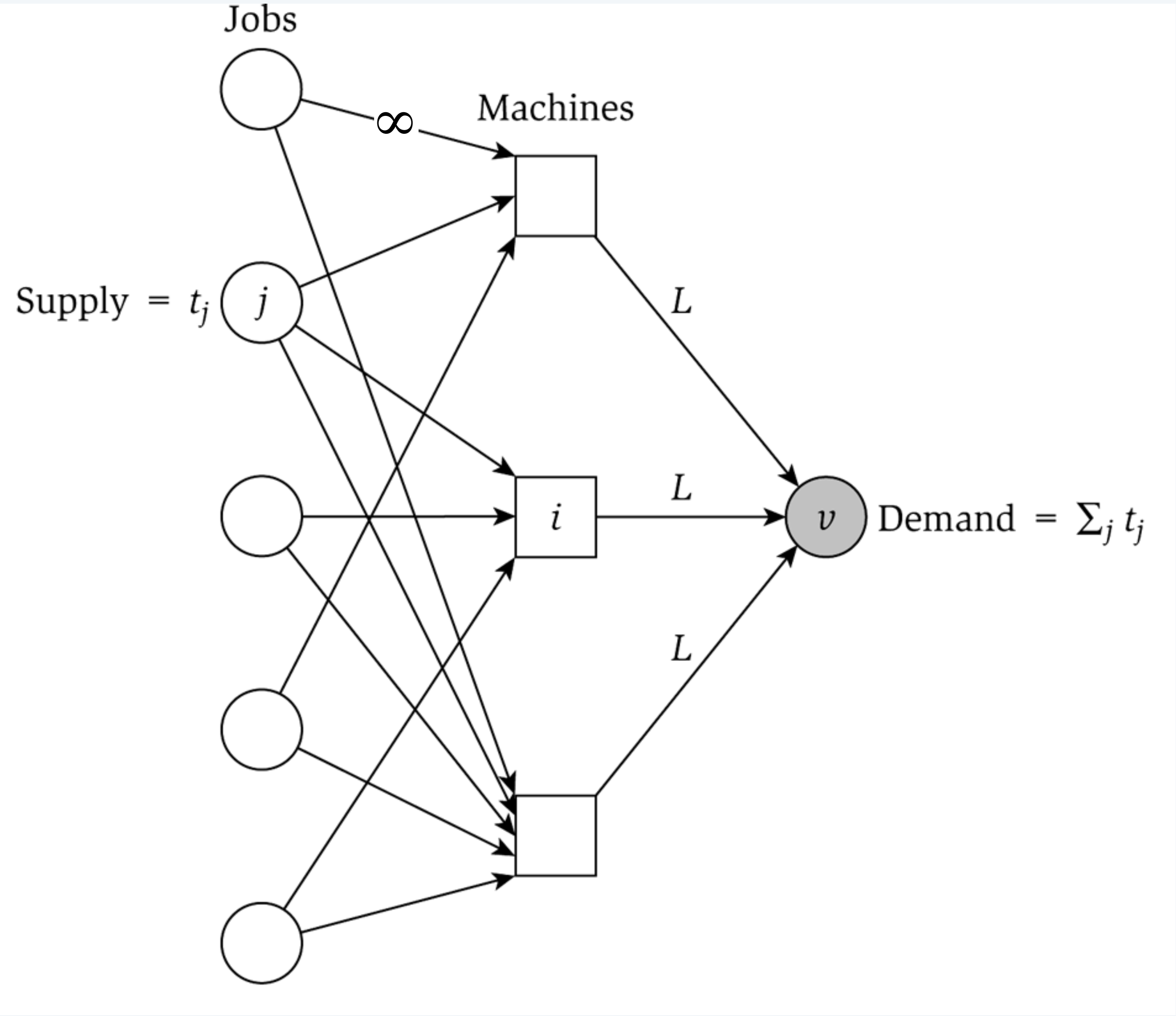
$$t_{\text{parent}(i)} \overset{\text{Lemma 1}}{\le} L^*$$

- Thus, the overall load $L_i \le 2L^*$. ▪

Generalized load balancing: flow formulation

Flow formulation of LP.

$$
\begin{array}{llll}
\sum_i x_{ij} & = & t_j & \text{for all } j \in J \\
\sum_j x_{ij} & \le & L & \text{for all } i \in M \\
x_{ij} & \ge & 0 & \text{for all } j \in J \text{ and } i \in M_j \\
x_{ij} & = & 0 & \text{for all } j \in J \text{ and } i \notin M_j
\end{array}
$$



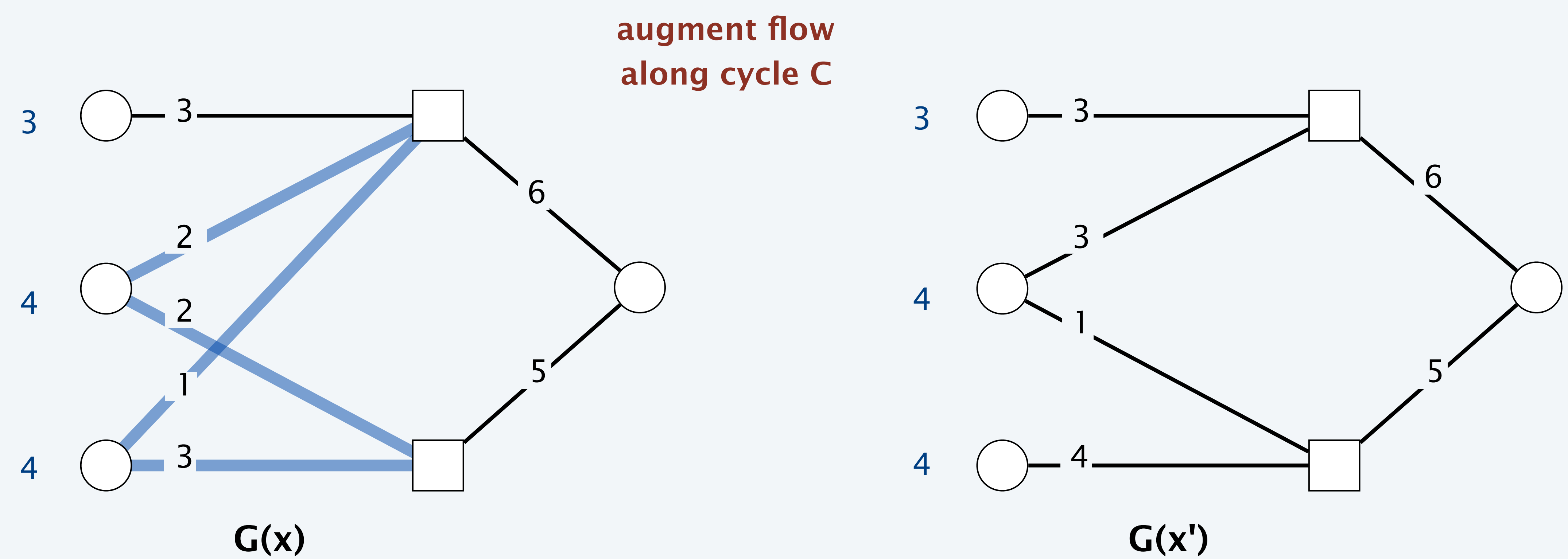
Observation. Solution to feasible flow problem with value L are in 1-to-1 correspondence with LP solutions of value L.

Generalized load balancing: structure of solution

Lemma 3. Let (x, L) be solution to LP. Let $G(x)$ be the graph with an edge from machine i to job j if $x_{ij} > 0$. We can find another solution (x', L) such that $G(x')$ is acyclic.

Pf. Let C be a cycle in $G(x)$.

- Augment flow along the cycle C. ← flow conservation maintained
- At least one edge from C is removed (and none are added).
- Repeat until $G(x')$ is acyclic. ▪



Conclusions

Running time. The bottleneck operation in our 2-approximation is solving one LP with $mn + 1$ variables.

Remark. Can solve LP using flow techniques on a graph with $m + n + 1$ nodes: given L, find feasible flow if it exists. Binary search to find L^*.

Extensions: unrelated parallel machines. [Lenstra-Shmoys-Tardos 1990]

- Job j takes t_{ij} time if processed on machine i.
- 2-approximation algorithm via LP rounding.
- If **P** ≠ **NP**, then no no ρ-approximation exists for any $\rho < 3/2$.

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APPROXIMATION ALGORITHMS FOR SCHEDULING UNRELATED PARALLEL MACHINES

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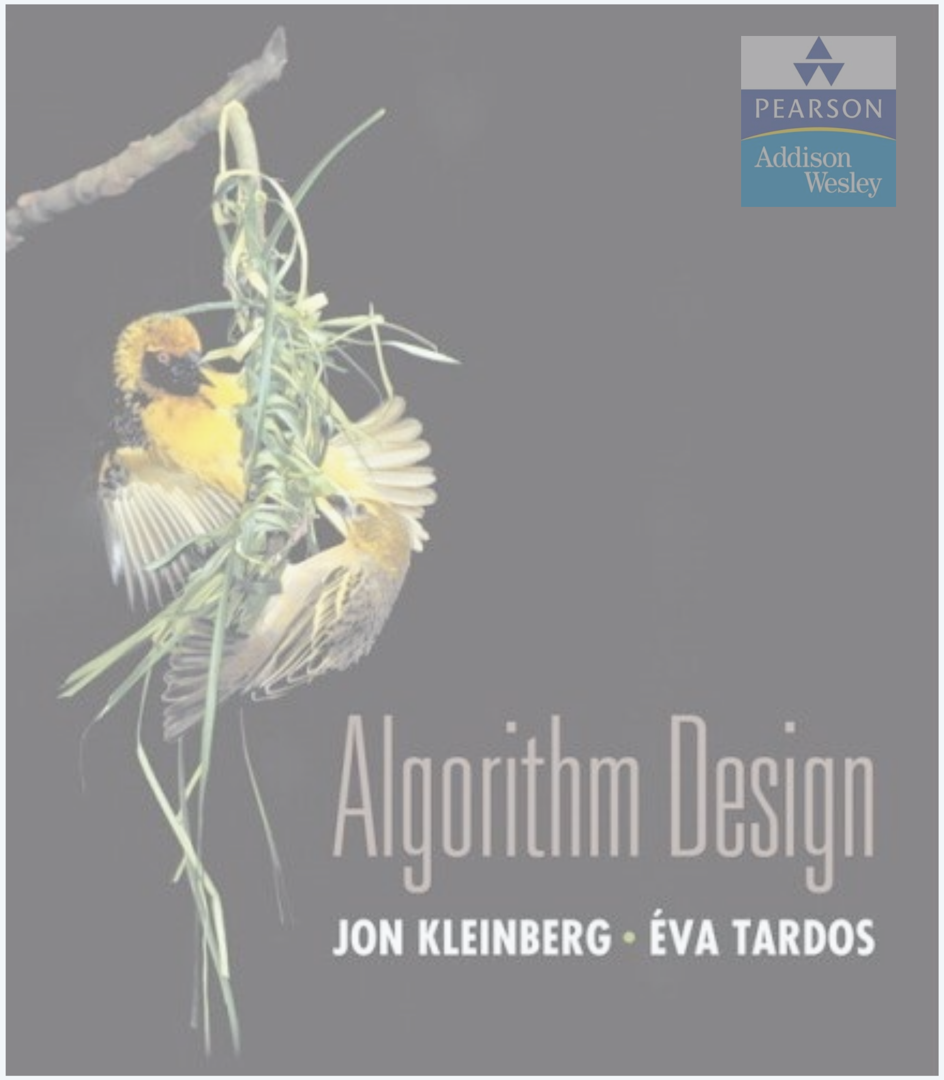

11. Approximation Algorithms

- load balancing
- center selection
- pricing method: vertex cover
- LP rounding: vertex cover
- generalized load balancing
- knapsack problem

Polynomial-time approximation scheme

PTAS. $(1 + \varepsilon)$-approximation algorithm for any constant $\varepsilon > 0$.

- Load balancing. [Hochbaum-Shmoys 1987]
- Euclidean TSP. [Arora, Mitchell 1996]

Consequence. PTAS produces arbitrarily high quality solution, but trades off accuracy for time.

This section. PTAS for knapsack problem via rounding and scaling.

Knapsack problem

Knapsack problem.

- Given n objects and a knapsack.
- Item i has value $v_i > 0$ and weighs $w_i > 0$. ← we assume $w_i \le W$ for each i
- Knapsack has weight limit W.
- Goal: fill knapsack so as to maximize total value.

Ex: $\{ 3, 4 \}$ has value 40.

item	value	weight
1	1	1
2	6	2
3	18	5
4	22	6
5	28	7

original instance (W = 11)

Knapsack is NP-complete

KNAPSACK. Given a set X, weights $w_i \geq 0$, values $v_i \geq 0$, a weight limit W, and a target value V, is there a subset $S \subseteq X$ such that:

$$\sum_{i \in S} w_i \leq W$$
$$\sum_{i \in S} v_i \geq V$$

SUBSET-SUM. Given a set X, values $u_i \geq 0$, and an integer U, is there a subset $S \subseteq X$ whose elements sum to exactly U ?

Theorem. SUBSET-SUM $\leq_P$ KNAPSACK.

Pf. Given instance $(u_1, \ldots, u_n, U)$ of SUBSET-SUM, create KNAPSACK instance:

$$v_i = w_i = u_i \qquad \sum_{i \in S} u_i \leq U$$
$$V = W = U \qquad \sum_{i \in S} u_i \geq U$$

Knapsack problem: dynamic programming I

Def. $OPT(i, w)$ = max value subset of items $1,..., i$ with weight limit w.

Case 1. OPT does not select item i.

- OPT selects best of $1, \ldots, i - 1$ using up to weight limit w.

Case 2. OPT selects item i.

- New weight limit = $w - w_i$.
- OPT selects best of $1, \ldots, i - 1$ using up to weight limit $w - w_i$.

$$OPT(i,w) = \begin{cases} 0 & \text{if } i = 0 \\ OPT(i-1,w) & \text{if } w_i > w \\ \max\{\, OPT(i-1,w),\quad v_i + OPT(i-1,w-w_i)\,\} & \text{otherwise} \end{cases}$$

Theorem. Computes the optimal value in $O(n\,W)$ time.

- Not polynomial in input size.
- Polynomial in input size if weights are small integers.

Knapsack problem: dynamic programming II

Def. $OPT(i, v)$ = min weight of a knapsack for which we can obtain a solution of value ≥ v using a subset of items $1, \ldots, i$.

Note. Optimal value is the largest value v such that $OPT(n, v) \leq W$.

Case 1. OPT does not select item i.

- OPT selects best of $1, \ldots, i-1$ that achieves value ≥ v.

Case 2. OPT selects item i.

- Consumes weight w_i, need to achieve value ≥ $v - v_i$.
- OPT selects best of $1, \ldots, i-1$ that achieves value ≥ $v - v_i$.

$$OPT(i, v) = \begin{cases} 0 & \text{if } v \leq 0 \\ \infty & \text{if } i = 0 \text{ and } \ v > 0 \\ \min \{OPT(i-1, v),\ w_i + OPT(i-1, v - v_i)\} & \text{otherwise} \end{cases}$$

Knapsack problem: dynamic programming II

Theorem. Dynamic programming algorithm II computes the optimal value in $O(n^2\, v_{max})$ time, where v_{max} is the maximum of any value.

Pf.

- The optimal value $V^* \le n\, v_{max}$.
- There is one subproblem for each item and for each value $v \le V^*$.
- It takes $O(1)$ time per subproblem. ▪

Remark 1. Not polynomial in input size!

Remark 2. Polynomial time if values are small integers.

Knapsack problem: polynomial-time approximation scheme

Intuition for approximation algorithm.

- Round all values up to lie in smaller range.
- Run dynamic programming algorithm II on rounded/scaled instance.
- Return optimal items in rounded instance.

item	value	weight
1	934221	1
2	5956342	2
3	17810013	5
4	21217800	6
5	27343199	7

original instance (W = 11)

item	value	weight
1	1	1
2	6	2
3	18	5
4	22	6
5	28	7

rounded instance (W = 11)

Knapsack problem: polynomial-time approximation scheme

Round up all values:

- $0 < \varepsilon \leq 1$ = precision parameter.
- v_{max} = largest value in original instance.
- θ = scaling factor = $\varepsilon \, v_{max} \, / \, 2n$.

$$\bar{v}_i = \left\lceil \frac{v_i}{\theta} \right\rceil \theta , \quad \hat{v}_i = \left\lceil \frac{v_i}{\theta} \right\rceil$$

Observation. Optimal solutions to problem with $\bar{v}$ are equivalent to optimal solutions to problem with $\hat{v}$.

Intuition. $\bar{v}$ close to v so optimal solution using $\bar{v}$ is nearly optimal; $\hat{v}$ small and integral so dynamic programming algorithm II is fast.

Knapsack problem: polynomial-time approximation scheme

Theorem. If S is solution found by rounding algorithm and S^* is any other feasible solution, then $(1+\epsilon)\sum_{i \in S} v_i \;\geq\; \sum_{i \in S^*} v_i$

Pf. Let S^* be any feasible solution satisfying weight constraint.

$$\begin{aligned}
\sum_{i \in S^*} v_i \;&\leq\; \sum_{i \in S^*} \bar{v}_i && \text{always round up} \\
&\leq\; \sum_{i \in S} \bar{v}_i && \text{solve rounded instance optimally} \\
&\leq\; \sum_{i \in S} (v_i + \theta) && \text{never round up by more than } \theta \\
&\leq\; \sum_{i \in S} v_i \;+\; n\theta && |S| \leq n \\
&=\; \sum_{i \in S} v_i \;+\; \tfrac{1}{2}\,\epsilon\, v_{max} && \theta = \varepsilon\, v_{max} / 2n \\
&\leq\; (1+\epsilon) \sum_{i \in S} v_i && v_{max} \leq 2\, \textstyle\sum_{i \in S} v_i
\end{aligned}$$

subset containing only the item of largest value

choosing $S^* = \{\, max \,\}$

$$\begin{aligned}
v_{max} \;&\leq\; \sum_{i \in S} v_i \;+\; \tfrac{1}{2}\,\epsilon\, v_{max} \\
&\leq\; \sum_{i \in S} v_i \;+\; \tfrac{1}{2}\, v_{max}
\end{aligned}$$

thus

$$v_{max} \;\leq\; 2 \sum_{i \in S} v_i$$

Knapsack problem: polynomial-time approximation scheme

Theorem. For any $\varepsilon > 0$, the rounding algorithm computes a feasible solution whose value is within a $(1 + \varepsilon)$ factor of the optimum in $O(n^3 / \varepsilon)$ time.

Pf.

- We have already proved the accuracy bound.
- Dynamic program II running time is $O(n^2\, \hat{v}_{\max})$, where

$$\hat{v}_{max} \;=\; \left\lceil \frac{v_{max}}{\theta} \right\rceil \;=\; \left\lceil \frac{2n}{\epsilon} \right\rceil$$