Kapitel 4: Approximation Algorithms

Inhalt:

- Greedy Techniques
 - Load-Balancing Problem
 - Center Selection Problem
- Pricing Method
 - Vertex Cover Problem
- Linear Programming and Rounding
 - Vertex Cover Problem
 - Generalized Load-Balancing Problem
- Polynomial Time Approximation Scheme
 - Knapsack Problem

Generalized Load Balancing

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

- Job j must run contiguously on an authorized machine in $M_j \subseteq M$.
- Job j has processing time t_i.
- 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 $L_i = \sum_{j \in J(i)} t_j$.

Def. The makespan is the maximum load on any machine = $\max_{i} L_{i}$.

Generalized load balancing problem. 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.

 $(IP) \min L$ s. t. $\sum_{i} x_{ij} = t_{j}$ for all $j \in J$ $\sum_{i} x_{ij} \leq L$ for all $i \in M$ $x_{ij} \in \{0, t_{j}\}$ for all $j \in J$ and $i \in M_{j}$ $x_{ij} = 0$ for all $j \in J$ and $i \notin M_{j}$

LP relaxation.

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

Generalized Load Balancing: Lower Bounds

Lemma 1. Let L be the optimal value to the LP. Then, the optimal makespan $L^* \ge L$. Pf. LP has fewer constraints than IP formulation.

Lemma 2. The optimal makespan $L^* \ge \max_j t_j$. Pf. Some machine must process the most time-consuming job. •

Probem: How can we do the rounding?

Generalized Load Balancing: Structure of LP Solution

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

Pf. (deferred)

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



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 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 j is a leaf, $x_{ij} = 0$ for all i \neq parent(j). 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. [Lenstra, Shmoys, Tardos 1990] Rounded solution is a 2-approximation.

Pf.

- Let J(i) be the jobs assigned to machine i.
- By Lemma 5+6, the load L_i on machine i has two components:



. Thus, the overall load $L_i \leq 2L^{\star}.$

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.
- No 3/2-approximation algorithm unless P = NP.

Generalized Load Balancing: Flow Formulation

Flow formulation of LP.



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

Fragen?



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Polynomial Time Approximation Scheme

PTAS. (1 + ε)-approximation algorithm for any constant ε > 0.

- Load balancing. [Hochbaum-Shmoys 1987]
- Euclidean TSP. [Arora 1996, 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 weights $w_i > 0$. \longleftarrow we'll assume $w_i \le W$
- Knapsack can carry weight up to W.
- Goal: fill knapsack so as to maximize total value.

	Item	Value	Weight
	1	1	1
1 - 11	2	6	2
/ = 11	3	18	5
	4	22	6
	5	28	7

Ex: { 3, 4 } has value 40.

Knapsack Problem: Dynamic Programming 1

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, ..., 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, ..., i-1 using up to weight limit w w_i

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

Running time. O(n W).

- W = weight limit.
- Not polynomial in input size!

Knapsack Problem: Dynamic Programming II

Def. OPT(i, v) = min weight subset of items 1, ..., i that yields value exactly v.

- Case 1: OPT does not select item i.
 - OPT selects best of 1, ..., i-1 that achieves exactly value v
- . Case 2: OPT selects item i.
 - consumes weight w_i , new value needed = $v v_i$
 - OPT selects best of 1, ..., i-1 that achieves exactly value v v_i

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

$$V^* \leq n v_{max}$$

Running time. $O(n V^*) = O(n^2 v_{max})$.

- V* = optimal value = maximum v such that $OPT(n, v) \le W$.
- Not polynomial in input size!

Knapsack: FPTAS

Intuition for approximation algorithm.

- Round all values up to lie in smaller range. v_i → v̂_i = [v_i/θ]
 Run dynamic programming algorithm on rounded instance. v̂_i
- Return optimal items in rounded instance.

	value	Weight		Item	Value	Weight
1	134,221	1		1	2	1
2	656,342	2		2	7	2
3	1,810,013	5		3	19	5
4 ;	22,217,800	6	$\theta = 100,000$	4	223	6
5 8	28,343,199	7		5	284	7

W = 11

W = 11

original instance

rounded instance

Knapsack: FPTAS

Knapsack FPTAS. Round up all values:

$$\hat{v}_i = \left\lceil \frac{v_i}{\theta} \right\rceil \qquad \qquad \overline{v}_i = \left\lceil \frac{v_i}{\theta} \right\rceil \theta$$

- v_{max} = largest value in original instance
- ϵ = precision parameter
- θ = scaling factor = $\epsilon v_{max} / n$

Observation. Optimal solution to problems with \overline{v} or \hat{v} are equivalent.

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

Running time. $O(n^3 / \epsilon)$.

- Dynamic program II running time is $O(n^2 \hat{v}_{max})$, where

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

Knapsack: FPTAS

Knapsack FPTAS. Round up all values: $\hat{v}_i = \begin{bmatrix} v_i \\ \theta \end{bmatrix} \quad v_i \le \overline{v}_i \le v_i + \theta$

Theorem. If S is solution found by our algorithm and S* is any other feasible solution then $(1+\varepsilon)\sum_{i \in S} v_i \ge \sum_{i \in S^*} v_i$

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

$$\begin{split} \sum_{i \in S^*} v_i &\leq \sum_{i \in S^*} \overline{v}_i \\ &\leq \sum_{i \in S} \overline{v}_i \\ &\leq \sum_{i \in S} (v_i + \theta) \\ &\leq \sum_{i \in S} (v_i + \theta) \\ &\leq \sum_{i \in S} v_i + n\theta \\ &\leq (1 + \varepsilon) \sum_{i \in S} v_i \\ &\leq (1 + \varepsilon) \sum_{i \in S} v_i \\ &\qquad n \theta = \varepsilon v_{\max} \text{ and } v_{\max} \leq \Sigma_{i \in S} v_i \end{split}$$

Fragen?

