

11 April 2025

Linear Programming & Knapsack

Plan

- * Analysis of Min Vertex Cover
- * Announcements
- * Knapsack

Minimum Weighted Vertex Cover

Given: Undirected Graph $G = (V, E)$

v/ vertex weights $W = \{w_v\}_{v \in V}$

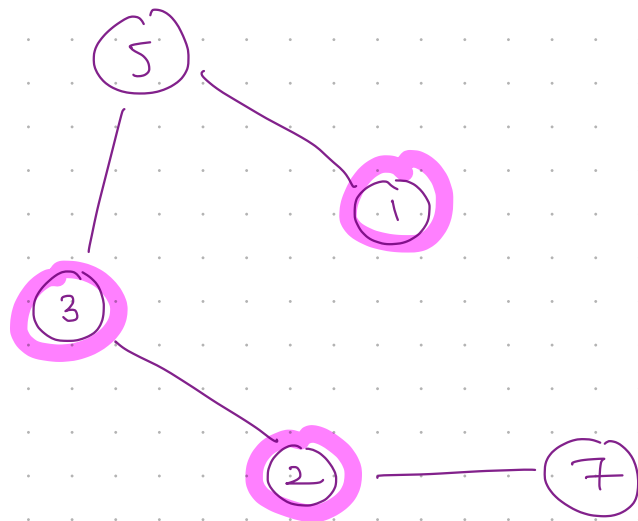
$$w_v \geq 0$$

Find: minimum weight

Vertex Cover

$$C \subseteq V$$

$$\sum_{v \in C} w_v$$



Approximate Minimum Weighted Vertex Cover

Given: Undirected Graph $G = (V, E)$
v/ vertex weights $W = \{w_v\}_{v \in V}$

$$w_v \geq 0$$

Find: approximately
minimum weight
Vertex Cover $C \subseteq V$

$$W(C) = \sum_{v \in C} w_v$$

$$W^*(G) = \min_{C^* \subseteq V} W(C^*)$$

Approximation Ratio
of Algorithm A
(for minimization
problem)

$$r_A = \max_G \frac{W(A(G))}{W^*(G)}$$

Integer Linear Programming

(NP-Hard)

variables

$x_1, x_2, \dots, x_n$

linear inequalities

$$\langle a_i, x \rangle = \sum_{j=1}^n a_{ij} x_j \leq b_i \quad i=1, \dots, m$$

integer constraints

$$x_j \in \mathbb{Z}$$

Linear optimization:

$$\text{Find } \min_{\vec{x}} \langle c, x \rangle = \sum_{j=1}^n c_j \cdot x_j$$

s.t. constraints,

Linear Programming

(Poly-time solvable!)

variables

$x_1, x_2, \dots, x_n$

$x_j \in \mathbb{R}$

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Linear Programming Relaxation

Min Wt. Vertex Cover ILP

Variables $\{x_v : v \in V\}$

Constraints

$$x_v \in \{0, 1\} \quad \forall v \in V.$$

$$x_u + x_v \geq 1 \quad \forall (u, v) \in E.$$

Objective

$$\min_{\vec{x}} \sum_{j=1}^n w_j \cdot x_j$$

Linear Programming Relaxation

Min Wt. Vertex Cover ~~ILP~~

Variables $\{x_v : v \in V\}$

Constraints

~~$x_v \in \{0, 1\} \quad \forall v \in V$~~

$0 \leq x_v \leq 1 \quad \forall v \in V$

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$\min_{\vec{x}} \sum_{j=1}^n w_j \cdot x_j$

Approximate VC

On input $G = (V, E)$, Construct & solve LP

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Then, ROUND solution

$$C = \emptyset$$

For $v \in V$.

$$\text{if } x_v \geq 1/2, \quad C \leftarrow C \cup \{v\}$$

Return C

Theorem: Approximate VC returns a 2-approximate VC.

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* For all edges $(u,v) \in E$ $x_u + x_v \geq 1$

$\Rightarrow$ at least one of $x_u, x_v \geq 1/2$

$\Rightarrow$ at least one of $u, v \in C$.

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$$W(C) = \sum w_j \cdot \mathbb{1}[x_j \geq 1/2]$$

$$\leq 2 \cdot \sum w_j \cdot x_j$$

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$$\leq 2 \cdot \text{OPT}(\text{VC-ILP}) = 2 \cdot [\text{Min wt. VC}]$$

Announcements

* HW 7 Out Now

* No recitation this weekend

Knapsack

Given: collection of n items U

* $w_i \equiv$ weight of i^{th} item

* $v_i \equiv$ value of i^{th} item

total capacity C

Find: Subset of items $S \subseteq U$

maximizing value $\sum_{i \in S} v_i$

s.t. weight limit $\sum_{i \in S} w_i \leq C$

5

7

4

2

11

3

4

3

10

6

15

4

A

B

C

D

E

F

$C = 16$

5

4

A

7

3

B

4

10

C

2

6

D

11

15

E

3

4

F

$$C = 16$$

$$S = \{E\}$$

$$V_s = 11$$

$$W_s = 15$$



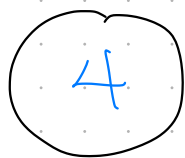
4

A



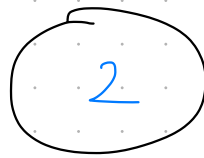
3

B



10

C



6

D



15

E



4

F

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Complexity of Knapsack

Theorem. Knapsack is NP-Hard.

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$$O(n^2 \cdot v^*)$$

where $v^* = \max_i v_i$

Complexity of Knapsack

Theorem. Knapsack is NP-Hard.

Theorem. There exists an algorithm for Knapsack that runs in time

$$O(n^2 \cdot v^*)$$

for integer values where $v^* = \max_i v_i$

Knapsack is Weakly NP-Hard.

* Reduction from SAT to Knapsack uses exponentially large values v_i !

Approximating Weakly NP-Hard Problems

Idea Reduce Knapsack to Knapsack

Approximating Weakly NP-Hard Problems

Idea

Reduce Knapsack to

Knapsack

large exact
values

small approximate
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Approximating Weakly NP-Hard Problems

Idea

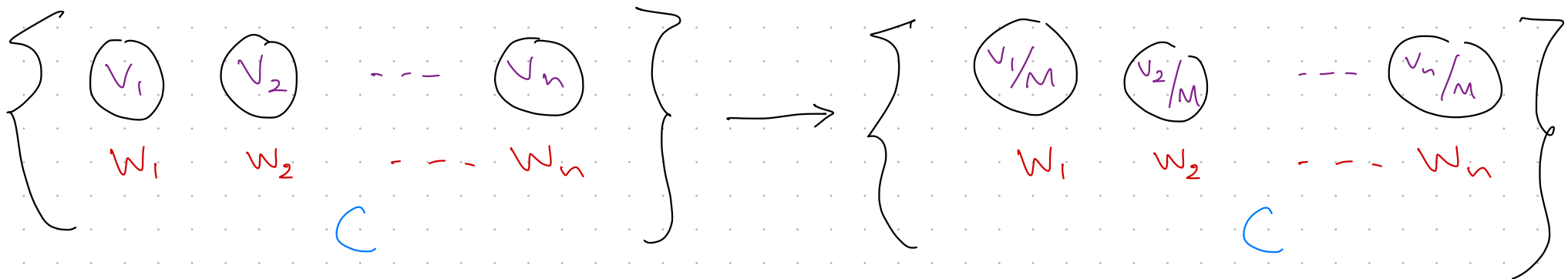
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Approach

Divide values by scaling factor M



Approx Knapsack ($\{v_i\}$, $\{w_i\}$, C)

* Scale values $\tilde{v}_i \leftarrow \left\lceil \frac{v_i}{M} \right\rceil$ for $i = 1 \dots m$

* $S \leftarrow \text{Exact Knapsack}(\{\tilde{v}_i\}, \{w_i\}, C)$

* Return S .

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$$\sum_{i \in S^*} v_i \leq \sum_{i \in S} v_i + n \cdot M$$

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By Exact Knapsack

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By Exact Knapsack

Approximation Ratio

$$\frac{\sum_{i \in S} v_i}{\sum_{i \in S^*} v_i} \geq \frac{\sum_{i \in S^*} v_i - n \cdot M}{\sum_{i \in S^*} v_i}$$

Running Time

Approximation Ratio

$$\frac{\sum_{i \in S} v_i}{\sum_{i \in S^*} v_i} \geq \frac{\sum_{i \in S^*} v_i - n \cdot M}{\sum_{i \in S^*} v_i}$$
$$\geq 1 - \frac{n \cdot M}{\max_i v_i} \quad (\text{assumes } w_i \leq C)$$

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(assumes $w_i \leq C$)

$$= 1 - \epsilon$$

$$\text{for } M \leq \frac{\epsilon \cdot \max_i v_i}{n}$$

Running Time

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Running Time

$$O\left(n^2 \cdot \max_i \left\lceil \frac{v_i}{M} \right\rceil\right)$$

Approximation Ratio

$$\begin{aligned} \frac{\sum_{i \in S} v_i}{\sum_{i \in S^*} v_i} &\geq \frac{\sum_{i \in S^*} v_i - n \cdot M}{\sum_{i \in S^*} v_i} \\ &\geq 1 - \frac{n \cdot M}{\max_i v_i} \quad (\text{assumes } w_i \leq C) \\ &= 1 - \epsilon \quad \text{for } M = \frac{\epsilon \cdot \max_i v_i}{n} \end{aligned}$$

Running Time

$$\begin{aligned} O\left(n^2 \cdot \max_i \left\lceil \frac{v_i}{M} \right\rceil\right) &\leq O\left(n^2 \cdot \left(\frac{\cancel{\max_i v_i}}{\cancel{\max_i v_i}} \cdot \frac{n}{\epsilon} \right)\right) \\ &= O(n^3 / \epsilon) \end{aligned}$$

Theorem. Knapsack has a Fully-Polynomial-Time Approximation Scheme (FPTAS)

↳ For any $\varepsilon > 0$, there exists an algorithm that $(1-\varepsilon)$ -approximates Knapsack running in $O(n^3/\varepsilon)$ time

Arbitrarily good approximation in polynomial time!